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Exploring the predictive validity of personality for job performance across occupations using a person-centered approach

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Abstract

Exploring the predictive validity of personality for job performance across occupations using a person-centered approach.

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The goal of this study is to shed light upon the complex and long-debated relationship between personality and job performance from a new angle. Using a person-centered approach to examine personality, this study is the first to examine the criterion-related validity of personality profiles in predicting job performance in a corporate sample while accounting for occupational membership. More specifically, using an archival dataset from a Fortune 100 company, the current study involves hypotheses and research questions related to the existence and distribution of personality profiles across occupations, incremental validity of personality profiles in predicting performance, differential predictive validity for personality profiles across occupations, and the distribution of personality profiles among top performers within occupations. Four organization-based personality profiles were identified: adaptable, rigid, confident, and nervous. Occupation-based personality profiles were also identified for the occupations of sales, accounting and finance, manufacturing engineering, and research and development. The identified occupation-based personality profiles included some of the organization-based profiles as well as some distinctive profiles. Testing for the criterion-related validity of personality profiles showed somewhat lower validities in comparison with personality traits. Examination of the incremental validity of personality profiles above and beyond personality traits showed limited evidence of incremental validity for organization-based profiles and mixed evidence for occupation-based profiles, with a few cases of notable incremental validity for occupation-based profiles in predicting specific job performance dimensions. In addition, an exploration of the distribution of personality profiles among the top 10% of performers indicated that the confident profile was most common and the rigid profile was least common. Theoretical and practical implications are discussed along with potential future research directions.

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Dedication

To my first daughter who was born the morning of June 19, 2019, just a few hours before my thesis proposal presentation… To the little one who attended my thesis defense on the same day she turned one month old… To the turquoise gemstone newly added to our small family... To *Fayrouz*.

Introduction

In an expanding and complex market, businesses strive to find, attract, and retain highly talented employees who can maintain and enhance their organizations' competitive advantage. This in turn has put much emphasis on the importance of understanding and advancing the area of personnel selection to meet this business need of selecting top performers. Researchers have long examined selection issues including studying assessment approaches, validity, and reliability, with the aim of identifying determinants of high job performance and maximizing prediction through various selection techniques.

Many selection studies have examined cognitive and non-cognitive predictors of job performance (see Cortina & Luchman, 2013). Although research provides strong support for cognitive ability, with evidence suggesting it is the best single predictor of job performance (e.g., Ree, Earles, & Teachout, 1994), many concerns are involved in relation to using measures of cognitive ability in practice given possible negative consequences, including adverse impact (see Hunter & Hunter, 1984). Therefore, substantial research attention has also focused on non-cognitive predictors of job performance in an attempt to effectively predict job performance while avoiding the undesired pitfalls of using cognitive ability measures. This has resulted in ongoing interest in one of the oldest and most debated non-cognitive predictor domains: personality.

There is no doubt that personality as a predictor of job performance has strong supporters who have advocated for the use of personality in selection (Ones, Dilchert, Viswesvaran, & Judge, 2007). On the other hand, other researchers and practitioners have been more skeptical of the use of personality as a predictor of performance, highlighting issues such as low criterion-related validity and faking potential (i.e., attempts by job applicants to fake responses to personality inventories to make themselves look better; Morgeson et al., 2007). The current research aims to contribute to this discussion by addressing three neglected issues that do not appear to have been focused on in previous research.

First, the debate on using personality as a predictor for job performance has been mainly based on dealing with personality as traits or variables that are used independently to examine relations between personality characteristics and job performance (trait-centered approach). However, a relatively new perspective on studying personality has recently emerged involving examining personality in its collective and whole nature by focusing on multiple personality traits (person-centered approach). This approach involves forming profiles of personality traits and may lead to a more comprehensive understanding of personality and its implications. Previous research has focused on exploring personality profiles outside of corporate organizational settings (e.g., school children; Chapman & Goldberg, 2011; undergraduate students; Daljeet et al., 2017; army recruits; Conte, Heffner, Roesch, & Aesen, 2017). Thus, the first objective of this research is to further examine this perspective by identifying personality profiles in a large multinational corporate sample and exploring the distribution of these profiles across occupations.

Second, the current research contributes to this area by examining whether personality profiles provide incremental validity in predicting job performance above and beyond personality traits. So far, only one published study has examined the validity of personality profiles in predicting performance (Conte, Heffner, Roesch, & Aesen, 2017) and no published studies have examined the incremental validity of personality profiles above personality traits.

Finally, the current study also examines the role of occupations in influencing the criterion-related validity of personality profiles in two possible ways. First, by including occupational membership as a potential moderator of personality profile validity, this study will examine if relationships with job performance may vary for participants across occupations based on occupational membership. Second, the study will also examine whether using each occupation separately to create occupation-based personality profiles (i.e., clustering based only on participants who belong to a specific occupation) might provide improved criterion-related validity, in comparison with organization-based personality profiles that are created using the whole-organization sample (i.e., clustering based on all participants within the organization regardless of their occupations).

Therefore, this study tries to reveal more about the complex relation between personality and job performance through using personality profiles and occupations to further understand prediction of job performance. By studying personality profiles and job performance across occupations, this study may further inform discussions regarding the extent to which the predictive value of personality in selection settings may tend to be underestimated.

The next section provides a review of literature to explain the constructs and theories related to this study and develop the hypotheses and research questions that this study addresses. Then, the methodology for the study will be explained, including the study type, participant characteristics, and the measures used. Results and discussion sections will be provided after that, in addition to a conclusion for the study.

Literature Review

Personality

According to Allport (1937), the term personality refers to the “the dynamic organization within the individual of those psychophysical systems that determine his [or her] unique adjustments to his [or her] environment" (p. 48). Personality is a part of our everyday language and philosophers and researchers have long debated its nature and implications. That is why there is no consensus regarding its definition or nature. Many efforts have been made in order to understand what personality is and researchers have attempted to provide explanations of the nature of personality by trying to develop models and taxonomies that characterize personality. These taxonomies vary in the number of factors and the hierarchical nature of personality characteristics (for an example of competing taxonomies of personality, see Borghans, Duckworth, Heckman, & Ter Weel, 2008).

One of the most prominent frameworks that has been adopted by researchers to study personality is the Five Factor Model (FFM), also known as the Big Five Model (Costa & McCrae, 1992a). This model is comprised of five main factors for describing personality, namely: conscientiousness, agreeableness, extraversion, openness to change, neuroticism (or emotional stability). This framework has been used in a large number of the personality studies, especially in organizational settings, with various scales based on it (e.g., NEO PI-R, Costa & McCrae, 1992b). This model has received some criticism (e.g., related to the lexical approach used in its development; see Hough, Oswald, & Ock, 2015). However, this model remains a prominent and useful approach to personality and thus it is also adopted in the current research.

The growing use of personality assessments in organizational settings has led to different ways of measuring personality. The most common method for assessing personality has been questionnaires, which could be rated by self or others (e.g., peers or supervisor). In addition to questionnaires, various other methods have been discussed in measuring personality such as interviews, biodata, assessment centers, virtual reality, genetic, and neurological testing (see Hough & Ones, 2002). Also, technology has provided us with innovative ways to assess personality. One of the new trends in assessing personality is using individuals' data available on social media websites. This provides researchers with huge amounts of data posted by individuals online which can be scraped, analyzed, and used for building predictive models using a large number of participants (e.g., Gerlach, Farb, Revelle, & Amaral, 2018; Gjurkovic & Jan Snajder, 2018).

All of these aspects of studying personality and measuring it has led to a great number of studies on the relation between personality and many outcomes. In industrial and organizational psychology, personality effects have been studied in relation to many areas including: job performance, career and occupational choice, organizational choice, training, job satisfaction, occupational health and safety, and leadership (Hough & Ones, 2002). Most of this research has used a variable-centered approach to study personality. However, recently another approach to studying personality has started to emerge: using a person-centered approach involving the examination of personality profiles.

Organization-Based Personality Profiles

Most of the history of personality research has focused on understanding this domain using a variable-centered approach (Asendorpf, 2002). This approach involves identifying personality traits and examining associations with important antecedents and outcomes. This has been a very productive and influential approach but can be limited insofar as it often involves studying traits in isolation. In contrast, recent interest in a more holistic understanding of how personality dimensions act together and combine in unique ways has led to more efforts to understand personality using a person-centered approach (Asendorpf, 2002; Ashton & Lee, 2009; Merz & Roesch, 2011). This approach is based on the notion that the same personality dimensions can exist in different configurations across individuals. Furthermore, these different configurations may form subpopulations within any population, where these subgroups are heterogeneous and distinctive from each other in terms of personality and may differ on a number of other variables.

Donnellan and Robins (2010) discussed several important advantages and challenges in studying personality through the lens of a person-centered approach. The advantages include that personality types provide a classification system and taxonomy that can increase knowledge by enabling researchers to focus on classes that share common characteristics. This approach also shifts our attention to the dynamic and integrated way in which personality traits combine to define every individual. In addition, some studies have demonstrated that this approach provides for not only reliable prediction of important outcomes (e.g., academic growth; see Hart, Atkins, & Fegley, 2003) but also incremental validity beyond the variable-centered approach (Asendorpf & Denissen, 2006). Finally, personality types can serve as efficient moderators that allow us to understand why individuals with similar levels on a specific personality variable have different responses to various events. However, challenges still exist for reaching consensus on the methodology used to identify types, statistical techniques suitable for extracting personality types (e.g., latent profile analysis, cluster analysis), and the source of personality ratings (e.g., informant, self-report, or behavioral ratings).

Literature in the last 20 years has supported the person-centered approach to personality. For example, three replicable personality profiles were first identified by Robins, John, Caspi, Moffitt, and Stouthamer-Loeber (1996): ego resilient, overcontroller, and undercontroller. Asendorpf, Borkenau, Ostendorf, and van Aken (2001) also found evidence of these three profiles in several studies that used measures of the Big Five Factors. The resilient type was characterized by low neuroticism and relatively high levels on the other traits; the overcontrolled type was characterized by high levels of neuroticism and low levels of extraversion; and the undercontrolled type was low in agreeableness and conscientiousness.

Researchers have also found similar patterns of three personality profiles in recent studies: well-adjusted, reserved, and excitable (Ferguson & Hull, 2018; Merz & Roesch, 2011). The well-adjusted profile was characterized by low levels of neuroticism and moderately high levels of the other four FFM factors (this could be compared to the previously discussed resilient type). The reserved profile was characterized by high neuroticism and conscientiousness and lower levels of the other three FFM factors (this could be compared to the previously discussed overcontroller type). The excitable profile was characterized by the highest levels of neuroticism, extraversion, and openness (this could be compared to the previously discussed undercontroller type).

A 4-profile solution was also found that identified the three profiles of resilient, overcontrolled, and undercontrolled, in addition to a fourth profile of bohemian that is characterized by low extraversion and conscientiousness (Honkaniemi, Feldt, Metsapelto, & Tolvanen, 2013). Furthermore, a 5-profile solution was also found which includes the following profiles: resilient, overcontrolled/rigid, reserved, undercontrolled/confident, and ordinary (Kinnunen et al., 2012; Zhang, Bray, Zhang, & Lanza, 2015). In an army sample (Conte, Heffner, Roesch, & Aasen, 2017), a 5-profile solution was found as well, which included the three profiles of resilient, overcontrolled, and undercontrolled, as well as two newly labeled profiles of amiable (high agreeableness and extraversion, low conscientiousness and openness) and conscientious/disagreeable (high conscientiousness and openness, low agreeableness). Finally, other studies have used personality frameworks other than the Big Five; for example, Daljeet, Bremner, Giammarco, Meyer, and Paunonen (2017) used the HEXACO model of personality and identified five profiles: Socially Considerate, Adventurous, Goal-oriented, Withdrawn, and Maladjusted.

Throughout these previous research attempts to explore personality profiles, the focus has been on examining profiles outside of the corporate population. For example, studies have investigated army recruits (Conte, Heffner, Roesch, & Aesen, 2017), undergraduate students (Daljeet et al., 2017), school children (Chapman & Goldberg, 2011), and broad adult samples (Kinnunen et al., 2012; Zhang, Bray, Zhang, & Lanza, 2015). Thus, one main objective of the current study is to extend this previous research by exploring personality profiles in a large multinational corporate sample and examining the distribution of these profiles across occupations. Based on prior findings, it appears quite likely that multiple profiles may be found (potentially in the range of three to five). However, given that results have been somewhat mixed, the number and nature of the profiles that might be observed is unclear. Thus, this will be examined empirically.

Hypothesis 1.1: Multiple organization-based personality profiles will be identified.

Job Performance

Organizations are on an endless quest to attract, select, train, and retain employees in order to perform tasks needed for the success of their businesses. Given this, job performance is not only the main outcome expected from employees, but also one of the most studied constructs in the organizational and management literature (see Murphy, Cleveland, & Hanscom, 2019; Wildman, Bedwell, Salas, & Smith-Jentsch, 2011). In examining job performance, researchers and organizations can focus on either behaviors or results; however, results can be a difficult target as employees may behave in the right way but circumstances that are out of employees' control could lead to less than desired results. That is why researchers typically define job performance through the lens of behavior, as employees can be responsible for their behaviors and direct them toward desirable organizational outcomes regardless of the final results. Murphy, Cleveland, and Hanscom (2019) define job performance as "the set of behaviors in the workplace that are relevant to achieving the legitimate goals of the individual, work unit, and organization" (p. 47).

In order to enhance our understanding of what constitutes job performance, researchers have developed several models. One of the most prominent models in the literature was developed by Campbell, McCloy, Oppler, and Sager (1993). In their theory, job performance is composed of the following eight dimensions: 1) job-specific task proficiency, 2) non-job-specific task proficiency, 3) written and oral communication, 4) demonstrating effort, 5) maintaining personal discipline, 6) facilitating peer and team performance, 7) supervision/leadership, 8) management/administration. It is also worth noting that these factors can be positively correlated and thus some researchers argue that there may be an overall job performance factor as well (Ree, Carretta, & Teachout, 2015; Viswesvaran, Schmidt, & Ones, 2005).

Moreover, as job performance is complex and multi-dimensional, Murphy, Cleveland, and Hanscom (2019) discussed that almost any job will be composed of a mix of the following types of work behaviors: 1) task performance or work behaviors that are essential for fulfilling the requirements of the job; 2) contextual/citizenship performance or work behaviors that aim at enhancing the job, the team, or the organization by providing support beyond the formal job needs; 3) adaptive performance or work behaviors related to adapting to emergencies or dealing with unexpected situations; 4) counter-productive workplace behavior or work behaviors that hinder the organization from achieving its goals by either harming the team or the organization or both (Robinson & Bennett, 1995), and 5) ethical performance or work behaviors that maintain and enhance the integrity of the organization (Russell et al., 2017).

To evaluate different levels of job performance, two types of evaluations can be done: objective evaluation and subjective evaluation. Objective evaluation refers to objective measures that are used to assess performance according to standards or measures that can be quantified. For instance, employees who work in the sales function usually have a sales target that they are expected to achieve, and this can be used as a standard unit for objectively assessing sales employees. On the other hand, subjective evaluations are typically made by managers or supervisors and they assess performance based on how much they believe the employees were able to demonstrate important work behaviors. Therefore, these are subjective in nature, based on the individual judgement, and can be affected negatively by different sources of rater errors, cognitive biases, and memory recall issues (e.g., Bernardin & Pence, 1980; Nathan & Tippins, 1990; Roch, Woehr, Mishra, & Kieszczynska, 2012).

Prediction of Job Performance by Personality

Given the importance of job performance to businesses, identifying factors that can significantly predict performance has been of particular interest to both practitioners and researchers. A large number of predictors, both cognitive and non-cognitive, have been studied in order to understand their relationship to job performance and how much of job performance variance they can account for. At the top of these predictors, cognitive ability has been found to be consistently positively related to job performance among many occupations (Ree, Earles, & Teachout, 1994). However, other undesirable outcomes often accompany the use of these cognitive measures. One important negative outcome is adverse impact. This refers to differential hiring rates that affect protected groups (e.g., gender, race) even if the hiring practices appear to be neutral in nature (see Hunter & Hunter, 1984). A substantial number of studies have also examined personality traits as predictors of performance. A meta-analysis by Judge et al. (2013) showed the following criterion-related validity values, corrected for unreliability in the predictor and the criterion, for the Big Five personality factors in predicting job performance: openness (.08), agreeableness (.17), emotional stability (.10), extraversion (.20), and conscientiousness (.26).

Researchers have debated the effectiveness of using personality in selection settings, including focusing on the level of criterion-related validity (e.g., Morgeson et al., 2007; Ones, Dilchert, Viswesvaran, & Judge, 2007; Tett & Christiansen, 2007). For example, some of the authors in Morgeson et al.'s (2007) discussion argued that personality tests have very low validity in predicting job performance, stating that the range of the uncorrected average correlations between personality measures and job performance is between -.02 and .15. They attributed higher reported validity estimates in the literature to extensive corrections or methodological weaknesses. On the other hand, Tett and Christiansen (2007) argued that using configural approaches to personality (e.g., personality profiles) and further examining situation specificity (which the current study proposes to address via considering occupational membership) can be expected to increase the criterion-related validity of personality. Given this, the current study attempts to address this issue by examining personality profiles and occupational membership to provide further insights regarding personality-performance relationships.

Incremental Validity of Personality Profiles for Job Performance

As noted, previous research has indicated that individual traits (e.g., conscientiousness) may provide at least modest prediction of performance. The current study examines the extent to which personality profiles can enhance the prediction of job performance by providing incremental validity over personality traits. Two lines of thought support this idea. First, although personality traits are the core element of our modern understanding to personality composition, no personality trait can be observed in isolation from the other traits that a person possesses. Any individual cannot be described using only one personality adjective, and human behavior can be observed as the manifestation of a combination of different levels of personality traits of that individual. Therefore, it is not only a natural occurrence but also a logical step to expect that a configuration of personality traits might better describe an individual than the mere addition of single traits that do not actually exist independently from each other within individuals. This is why that natural existence of a configuration of personality traits within individuals could be expected to be more predictive of behaviors (in this case job performance) than using a traditional variable-centered approach involving scores on independent personality variables (traits). This is in accordance with a previous call from Block's (1971):

> "In the realm of personality psychology, a preoccupation with variables per se also seems to be dominant. Psychologists of personality often write of the correlation between variables, somehow without explicit recognition that these variables are represented and system-organized within persons. Variable-centered analyses are useful for understanding the differences between people and what characteristics go with what characteristics in a group of individuals. But as well, and ultimately, psychology will need to seek understanding of the configuration and systematic connection of personality variables as these dynamically operate within a particular person" (p. 12-13).

Second, the existence of personality traits in these different configurations likely has important consequences. When these personality traits co-exist in an individual at different levels, these traits can change the effects of one another and the mutual manifestation of these traits can collectively shape the final observable outcomes, which is the result of what is known as trait interactions. As noted by Witt, Burke, Barrick, and Mount (2002), "certain personality traits may interact with others to result in desirable, as well as undesirable, workplace behaviors" (p. 164). Many researchers have observed how certain traits interact with others, leading to behavioral outcomes that are different from what would be expected from the effect of a single personality trait (see Shoss & Witt, 2013). For example, although conscientiousness has repeatedly been found to correlate positively with job performance (e.g., Barrick & Mount, 2005; Mount & Barrick, 1995; Salgado, 1997), Witt et al. (2002) found that the positive effect of conscientiousness on job performance depends on the level of agreeableness, such that individuals who had high levels of conscientiousness accompanied by low levels of agreeableness received lower job performance ratings.

Another approach for studying trait interactions in the literature is the Circumplex Model (i.e., Abridged Big Five Dimensional Circumplex, AB5C; Hofstee, De Raad, & Goldberg, 1992). This circular model that is based on the Big Five dimensions allows for mapping lower-order personality traits at the intersection between two Big Five dimensions. This location reflects the primary and secondary loading of these traits on the two corresponding Big Five factors, creating a blend of personality traits based on the intersection of Big Five dimensions. A useful example to show the potential importance of using these trait blends in relation to job performance involves examining two blends of conscientiousness: purposefulness (high conscientiousness and high emotional stability) versus perfectionism (high conscientiousness and low emotional stability), where the former can be a desirable workplace behavior while the latter may be undesirable (Hewitt & Flett, 1991; Johnson & Ostendorf, 1993; see Shoss & Witt, 2013). Also, although both extraversion and emotional stability have demonstrated low positive correlations with job performance (Barrick & Mount, 2001), the interaction of these two Big Five factors (resembling happiness) was found to be more predictive of job performance than either of them individually for customer service employees (Judge & Erez, 2007).

Furthermore, a more comprehensive example was provided by Burns, Morris, and Wright (2014) where both the circumplex trait of dutifulness and the corresponding trait interaction between agreeableness and conscientiousness were simultaneously significant predictors of counter-productive work behaviors (CWBs), suggesting that both circumplex traits and interactions are synergistic approaches to the Big Five traits that offer further understanding for the complex effect of personality on workplace outcomes. Hence, all these implications of trait interactions collectively provide a second reason why configural approaches (e.g., personality profiles) could better explain important workplace outcomes, and possibly provide incremental validity in predicting job performance over personality traits.

Unlike the configural approach of personality profiles, trait interactions can be hard to detect and interpret due to their complexity (McClelland & Judd, 1993). Personality profiles can be an excellent configural approach to study personality, as issues related to interactions can be more easily addressed through the lens of identified personality profiles (Asendorpf, 2015; Daljeet et al., 2017). Tett and Christiansen (2007) have indeed called for "configural analysis of trait-performance linkages in terms of personality profiles" (p. 979) given the potential for improved criterion-related validity over available estimates based on the variable-centered approach. The practical implications of this call were to a limited extent referred to by Kulas (2013) whose study found that 62% of surveyed selection-oriented consultative vendor organizations do already implement some form of profile matching. Yet, despite the importance of uncovering the criterion-related validity of personality profiles in predicting job performance, most of the existing research on personality profiles examines their predictive ability for criteria other than job performance. For example, research has examined self-efficacy, work engagement, and job satisfaction (Perera, Granziera, & McIlveen, 2018); self-concept (Pilarska, 2018); social relationships and temperamental outcomes (Asendorpf & Denissen, 2006); academic achievement and behavior in children (Hart, Atkins, & Fegley, 2003); and intrinsic career outcomes (De Fruyt, 2002).

However, to the best of our knowledge, only one published study has examined the criterion-related validity of personality profiles in predicting job performance (Conte, Heffner, Roesch, & Aesen, 2017). In this study, Conte and colleagues found that there were significant differences across the five identified personality profiles for the performance dimension of discipline, but not for the dimension of effort. The personality profile of resilients had a significantly higher rating for discipline than the overcontrolled, amiable, and undercontrolled profiles; in addition, the conscientious/disagreeable profile had a significantly higher rating for discipline than the undercontrolled profile. However, this study did not investigate incremental validity over the common personality traits approach. Additional searching yielded only four other unpublished studies that have explored the relationship between personality profiles and job performance (Early, 2016; Criswell, 2013; Shen, 2011; as cited by Shen, 2011: Waters & Sackett, 2006). These studies produced mixed results in terms of the incremental validity of personality profiles over personality traits, as findings ranged from having no incremental validity for personality profiles to having weak support for incremental validity above and beyond the common variable-centered approach.

Therefore, the second objective of the current study is to contribute to the very limited research on the relationship between personality profiles and job performance. More specifically, this study investigates personality profiles in terms of criterion-related validity and incremental validity over personality traits to better inform researchers and practitioners on the effectiveness of both approaches in predicting job performance in a multinational corporate sample.

Hypothesis 1.2: Organization-based personality profiles will have a contribution above and beyond personality traits in predicting organization-wide job performance.

Person-Environment Fit

One of the most salient goals in organizational research and practice is to achieve the best possible person-environment fit. According to Kristof-Brown, Zimmerman, and Johnson (2005), "PE fit is broadly defined as the compatibility between an individual and a work environment that occurs when their characteristics are well matched" (p. 281). This congruence between the individuals and the environment is important because it may have significant consequences (e.g., satisfaction, performance, and turnover) and the better the fit, the better the outcomes (Su, Murdock, & Rounds, 2015; van Vianen, 2018). The process of fitting individuals with environments is dynamic and reciprocal where individuals seek to change their environments to have a better fit, and their environments (e.g., organizations) seek to shape individuals to achieve this fit (Rounds & Tracey, 1990).

The person part of the person-environment fit (PE fit) can refer to various aspects of individuals that vary across people including personality, vocational interests, values, and abilities. These individual differences can interact with different aspects of the environment as well, such as occupations, organizations, groups, and supervisors, leading to a variety of PE fit forms (i.e., person-job fit, person-occupation fit, person-organization fit, person-group fit, and person-supervisor fit). A meta-analysis study by Kristof-Brown, Zimmerman, and Johnson (2005) shows important relations between each of these types of PE fit and important organizational outcomes, supporting the concept behind maximizing PE fit to obtain better organizational outcomes.

Person-Occupation Fit

One of the dimensions of PE fit that first comes to mind in explaining the match between the right individuals and the right environments is person-job fit. This type of fit is defined as "the congruence between an individual's KSAs and the KSAs required by the job, or the wishes of the individual and the attributes of the job" (Kristof, 1996, p. 3). Simply put, when the knowledge, skills, experience, and personal characteristics of an individual match a specific job, it is said that this person has a good fit to the job. This, of course, can refer to the match between individual's personality and the requirements of the job. However, because a single occupation can be comprised of subgroups of several narrow jobs, the construct of person-occupation fit (or person-vocation fit; Holland, 1997) is more suitable for the purpose of the current study. Person-occupation fit refers to the match between an individual and an occupation such that the occupation suits the person's characteristics and the person can fulfill its requirements and duties in a successful manner. In the following section, the occupational role in person-occupation fit will be discussed.

Occupations

The term occupation is basically derived from the verb occupy, referring to an entity within which individuals are situated (Dierdorff, 2019). A useful operational definition of occupations was provided by Dierdorff et al. (2009): "collections of work roles with similar goals that require the performance of distinctive activities as well as the application of specialized skills or knowledge to accomplish these goals" (p. 974). Dierdorff (2019) discussed the evolution of occupations in the work literature and reviewed many reasons why using an occupational perspective may be very informative for studying work and workers. Dierdorff mentions that occupations had an important role in understanding worker behaviors and attitudes for a long time dating back to the beginnings of the twentieth century (e.g., Parsons, 1909), but during the 1960s and 1970s the focus shifted instead to be on organizations.

Dierdorff (2019) discussed four reasons behind the need to revitalize an occupational focus. First, occupations have their unique cultures within which individuals are provided with a context that guides their social environments, meaning of work, and control of work life. These occupational cultures involve communities of practitioners that share common attributes (e.g., knowledge, skills, and abilities) and occupation-related experiences. Second, the changing nature of work supports more utilization of an occupational lens to study workers since they are no longer attached to organizations for their lifetime and can keep their occupational expertise regardless of the organization at which they are working or even in cases where they are doing freelance work. Third, occupations are related to many important organizational behavior variables, and for some outcomes they may have more influence than organizations, such that individual differences cluster around occupations more than organizations (Landy, 1972; King et al., 2017). Finally, the organizational orientation in research is now much more mature and saturated, whereas studies using the occupational lens may provide us with novel insights and understanding of work and workers.

The current research draws from this perspective, viewing occupations as a unique and directly relevant environment for studying personality. In particular, this study examines the extent to which personality profile criterion-related validity may differ across occupations. The issue of validity differing across situations was raised by Tett and Christiansen (2007) in their discussion of the low criterion-related validity of personality often observed. They called for carefully considering situational specificity in order to address this personality validity issue. Situational specificity can be seen when the relationships between personality and job performance are stronger or weaker based on the extent that a work situation (e.g., tasks) offers cues for expressing specific personality attributes. This interaction between a person's trait and a situation (i.e., situational specificity) is therefore important to be considered when using personality in selection settings (Shoss & Witt, 2013; Tett, Jackson, & Rothstein, 1991). Accordingly, the unique context and culture of each occupation can be a rich representation of both the tasks involved and the characteristics required for a specific occupation, leading to a more detailed work-related situation within which relevant traits can be observed. This suggests each occupation may provide a situation that allows for relevant personality-performance linkages to be more clearly expressed.

In support of occupations influencing personality prediction, evidence suggests personality-performance relationships may differ across occupational groups. Perhaps Barrick and Mount's (1991, 2001) meta-analysis studies are the most prominent in exploring the relationship between personality attributes and job performance across many occupations, where they found that some personality traits were more predictive of performance in specific occupations. Although they found that some personality dimensions were important across occupations (e.g., conscientiousness), they also reported that extraversion was a predictor for job performance in people-oriented occupations such as management (r = .21),police work (r = .12), and sales (r = .11) but less predictive in other occupational groups. This finding was also supported by Salgado (1997). In addition, Hurtz and Donovan's (2000) meta-analysis also indicated differences in prediction across four occupations, where agreeableness was more positively correlated with customer service performance, while emotional stability and extraversion were more positively correlated with sales performance. These examples collectively suggest that occupations play an important role in moderating the relationship between personality and job performance, in line with the propositions of person-occupation fit and occupational situational specificity. As a result, I hypothesize that occupations (or occupational membership) may moderate the relationship between personality profiles and job performance.

Hypothesis 1.3: Occupations will moderate the relationship between organization-based personality profiles and job performance.

Occupation-Based Personality Profiles

As previously discussed, person-occupation fit refers to the match between an individual and a specific occupation that suits the person's traits and for which the person can have a tendency to fulfill the requirements and perform duties in a way that matches his/her strengths. This matching can be driven to a great extent by individuals' personality in that individuals may try to find an occupation that fits their traits and natural dispositions. For instance, Lion (1997) has found a longitudinal, causal relationship between personality and job facet-choice. In this way, personality is an important factor that could affect the way individuals shape their environment to reach PE fit over their lifetime, in a process that could be explained in light of two frameworks: occupational gravitation and attraction-selection-attrition (ASA).

The hypothesis of occupational gravitation proposes that individuals will seek to change their occupations throughout their career to achieve a match between their personalities, interests, and abilities and their occupation (Wilk, Desmarais, & Sackett, 1995). This concept was primarily a reflection of the theory of vocational choice (Holland, 1973, 1985, 1997). The notion is that individuals can reflect on which occupations can be a good match for their personalities and attributes and hence try to seek out occupations in the hope that they gradually improve their person-occupation fit (Keiser, 2018). This involves applying to different jobs at various organizations to land an opportunity that may suit their characteristics. This iterative process takes place with the aim of achieving different types of PE fit including person-occupation fit. One of the results of this process is that individuals who match better with occupations or organizations can be attracted and retained at such matching environments, which could increase the likelihood of having similar personalities within occupations and organizations.

Schneider’s (1987) framework of attraction-selection-attrition (ASA) provides an important complementary explanation for researchers and organizations on the dynamic role of organizations in attracting and retaining employees for a specific environment. This ASA framework proposes that both individuals and organizations who are more alike and matching are attracted to each other, leading to organizations selecting the most matching individuals. In the case of having a poor match between individuals and organizations, either of individuals or organizations could end the working relationship through attrition that takes place by quitting the job (for individuals) or laying off the individual (for organizations). These continuous efforts of iterative matching by both individuals and organizations would lead to maintaining an enhanced PE fit. Therefore, both occupational gravitation (from employees’ perspective) and the ASA framework (from organizations’ perspective) suggest that there will be similarity or homogeneity of characteristics for those who end up in the same occupation or organization. Researchers have used this concept to focus on two directions of research: (a) identifying a modal personality profile that may best represent incumbents of each occupation, and (b) examining the notion of homogeneity at an organizational level and at an occupational level.

First, many studies have tried to identify the pattern of personality attributes that is common for individuals who belong to a specific occupation with the aim of describing what the modal personality profile of a good performer in this occupation may look like. One way of doing this is by showing the mean scores for an occupation's successful incumbents across various personality traits to form a representative personality profile of this occupation (Schmitt, 2014). For example, studies have explored a modal configuration of personality traits for occupational therapists (Peacock & O'Shea, 1984), police officers (Twersky-Glasner, 2005), chemists, ministers, and career military officers (Siegelman & Peck, 1960), and teachers (May, 1968). Possibly the most comprehensive and systematic recent effort in this regard is the one provided by the Occupational Information Network (O*NET; Peterson, Mumford, Borman, Jeanneret, & Fleishman, 1999), which includes the results of periodic data collection on different information categories including work styles (i.e., workplace-relevant personality traits) for more than 800 occupations. This data collection has resulted in mean ratings of importance for 16 personality sub-dimensions across these occupations listed within this database. All of these research efforts have collectively suggested the importance of identifying modal personality profiles for occupations, guided by the implications of the person-occupation fit framework. However, this research direction of using the modal personality profile in selection of successful candidates for an occupation can result in a potential drawback in terms of attempts to increase organizational diversity (Kulas, 2013).

Second, research studies have also proceeded with investigating another direction for person-occupation fit by examining the existence of personality homogeneity in occupations and organizations. This has been supported by various studies for both occupations and organizations (e.g., King et al., 2017; Ployhart, Weekley, & Baughman, 2006; Satterwhite, Fleenor, Braddy, Feldman, & Hoopes, 2009). These studies found that occupational homogeneity was significantly greater than organizational homogeneity. However, the reported personality homogeneity statistics within occupations were not high values. For instance, Ployhart, Weekley, and Baughman (2006) found that occupational grouping accounted for 17%, 24%, 17%, and 20% of the variance in emotional stability, extraversion, agreeableness, and conscientiousness, respectively. In line with that, King et al. (2017) found that occupational grouping accounted for 4%, 6%, and 3% in emotional stability, extraversion, and conscientiousness, respectively. This shows lower values than the Ployhart et al. (2006) findings possibly because of having more variation in the sample. Although this evidence supports the concept of occupational personality homogeneity, it also suggests there may not be a single personality profile for representing occupations.

Therefore, these two areas of research suggest that occupations may often contain multiple prominent personality profiles. Consistent with this idea, recent research has found support for identifying personality profiles within an occupation. For instance, Perera, Granziera, and McIlveen (2018) have identified four distinct personality profiles of teachers: rigid, ordinary, well-adjusted, and excitable. These researchers also found meaningful differences in terms of outcomes (e.g., self-efficacy, work engagement, and job satisfaction) across the identified personality profiles. In line with these findings, I hypothesize that by diving deeper inside occupations, multiple occupation-relevant personality profiles can be found. This analysis should lead to creating occupation-based personality profiles based on the sample of incumbents within an occupation.

Hypothesis 2.1: Multiple occupation-based personality profiles will be identified.

In addition, it is expected that the identification of these personality profiles within an occupation may reveal more nuanced differences in personality profiles as compared to personality profiles created based on the whole organizational sample for two reasons. First, organization-based personality profiles are developed based on a larger sample and may be influenced by an uneven distribution of incumbents across occupations such that a larger representation of incumbents in specific occupations may exist along with a smaller representation of incumbents of other occupations. In this case, the incumbents of occupations with a relatively major representation in the dataset could have more of an influence on the final set of organization-based personality profiles which in turn can possibly prevent us from observing the nuanced details of personality profiles for incumbents of relatively less represented occupations in the dataset. Accordingly, creating personality profiles within occupations may allow us to avoid this problem of obstructing nuanced differences in personality profiles. This may then provide a more accurate representation of incumbents of an occupation, and possibly a better prediction of job performance for these specific occupations.

Second, by creating occupation-based personality profiles, we may argue that we follow a process that is conceptually similar to developing personality-related job analysis information (Costa, McCrae, & Kay, 1995; Goffin et al., 2011; Raymark, Schmit, & Guion, 1997; Sumer, Sumer, Demirutku, & Cifci, 2001). This approach builds on conducting a typical job analysis by using subject matter experts (e.g., incumbents, supervisors, or consultants) in order to identify job-related relationships between the tasks of the job and the corresponding personality traits that help individuals perform these tasks. Identifying these customized personality-performance linkages within occupations aims to focus on personality characteristics directly relevant to the job of interest, which may then lead to stronger relationships between personality and job performance. In line with the suggestion of Jenkins and Griffith (2004) regarding "the necessity to perform personality based job analysis within a specific occupational category to properly select a personality measure" (p. 255), in the current study I follow a conceptually similar approach by directly exploring the personality profiles of incumbents within occupations. This may then facilitate the identification of occupation-relevant personality characteristics, and as a result lead to observing stronger relationships between personality profiles and occupation-specific job performance. This level of occupational specificity in identifying configurations of personality profiles cannot be achieved using the less occupation-specific organization-based profiles. Therefore, I hypothesize that developing personality profiles for incumbents within occupations (occupation-based personality profiles) may allow for improved prediction of performance beyond that provided by organization-based profiles or personality traits.

Hypothesis 2.2: Occupation-based personality profiles will have a contribution above and beyond both personality traits and organization-based personality profiles in predicting job performance.

Finally, the current study also allows for the exploration an additional issue that is likely to be of interest to organizations. Specifically, the current dataset can be used to explore the characteristics of top performers. O'Boyle and Aguinis (2012) found that there were a small number of top performers who were responsible for a major proportion of organizational outcomes and that their performance level was substantially above the average performance level. Accordingly, given the importance of identifying, attracting, and retaining top performers for organizations, we may extend the investigation of occupation-based personality profiles in the current dataset to further explore the following questions: How are these personality profiles represented in the top 10% of performers within the organization and within occupations? Are personality profiles equally represented within the top 10% of performers? Or does one of the personality profiles (or more) dominate within the top performers?

Research Question: What is the distribution of personality profiles for the top 10% of performers in the organization and within occupations?

Methodology

Participants

The current study uses an archival dataset from a concurrent validity study conducted at an American Fortune 100 multinational consumer goods corporation. A representative sample of the company employees across different countries and regions participated in the study. Employees responded to personality items and their supervisors rated their job performance across the nine dimensions of the organization's competency model.

Participants were 4653 employees. During analysis, 516 participants were excluded due to missing data and outliers, as explained in more detail in the results section. The final number of participants used for analysis was 4137. The sample was 43% female. Out of 38.2% who chose to report their race, 78.2% were white, 8.5% were Asian, 6.4% were Hispanic, and 6.3% were black. In terms of education, .2% of the participants did not have a High school degree, 3.5% had a High school or equivalent degree, 3.1% had an Associate's or equivalent degree, 49.6% had a Bachelor's degree, 34.5% had a Master's degree, 8.3% had a Doctoral degree, and .9% had other professional degree. Although this study represents participants from 72 countries, the largest percentage of participants were American (40.1%). Finally, the sample participants were surveyed with the following regional participation percentages: 42.4% from North America; 28.7% from Europe, Middle East, and Africa; 17.4% from Asia-Pacific; and 11.4% from Latin America.

Measures

Personality

Participants completed a set of 136 proprietary personality assessment items that were rated using a 1 to 5 Likert-type scale from 1 (very inaccurate) to 5 (very accurate). These items were subsequently organized and mapped on to the Big Five framework to facilitate comparison with other studies. First, the items that were found to be originally from other Big Five measures were sorted into the corresponding Big Five dimensions. Second, two industrial-organizational psychology graduate students rationally categorized the remaining personality items into Big Five dimensions. Third, the items that were sorted into the Big Five dimensions in the previous two steps (55 items) were used in an online convergent validity study along with a 50-item IPIP Big Five measure. The two scales were given to a sample of 172 participants from Amazon's Mechanical Turk. The results obtained were then used to further reduce the number of personality items that match with the IPIP Big Five to 41 items. The convergent validities for this 41-item measure were adequate as reported in Table 1.

Table 1

MTurk's Convergent Validities for Organization's Personality Scale and the IPIP Scale

Variable	*M*	*SD*	1	2	3	4	5	6	7	8	9	10
1. IPIP Openness to Experience	3.82	0.71	(.86)									
2. IPIP Conscientiousness	3.84	0.68	.27**	(.81)								
3. IPIP Extraversion	2.87	1.00	.28**	.28**	(.92)							
4. IPIP Agreeableness	3.83	0.79	.27**	.37**	.17**	(.89)						
5. IPIP Emotional Stability	3.49	0.94	.23**	.44**	.35**	.13	(.91)					
6. Organization Openness	3.90	0.60	.77**	.34**	.29**	.34**	.23**	(.84)				
7. Organization Conscientiousness	4.01	0.61	.37**	.70**	.24**	.44**	.40**	.49**	(.85)			
8. Organization Extraversion	3.19	0.70	.44**	.44**	.67**	.12	.38**	.48**	.41**	(.66)		
9. Organization Agreeableness	3.73	0.65	.24**	.42**	.23**	.79**	.19*	.38**	.47**	.19*	(.85)	
10. Organization Neuroticism	2.71	0.65	-.37**	-.42**	-.43**	-.17**	-.73**	-.37**	-.37**	-.52**	-.28**	(.68)

Note. $^{*}p < .05$, $^{**}p < .01$. Cronbach's alpha noted on diagonal in parentheses.

Based on results from this data collection, these 41 items representing the Big Five model were deemed appropriate to use for the current study. The breakdown of these items and their corresponding scale reliabilities for the current study are: 10 items for openness (alpha = .73), 10 items for agreeableness (alpha = .77), 9 items for conscientiousness (alpha = .70), 5 items for extraversion (alpha = .55), and 7 items for neuroticism (alpha = .60).

Job Performance

The organization went through a job analysis project, implemented by internal industrial-organizational psychologists, which resulted in the creation of an organization-specific competency model. This competency model is comprised of nine dimensions of job performance (see Table 2).

Supervisors rated study participants on these dimensions. These ratings were obtained using five-point scales from 1 (Weak) to 5 (Exceptional) or from 1 (Always) to 5 (Never), using five to six items to rate each dimension. The reliabilities for these job performance dimensions in the current study range from .69 to .83.

Table 2

Organization's Competency Model Job Performance Dimensions

Dimension	Definition
Thinks and Acts Decisively	Integrates Knowledge and Thinks Strategically, Analyzes Information and Solves Problems, Uses Judgment, Makes Timely Decisions.
Leverages Mastery	Applies Mastery, Understands the Business, Understands the Organization, Possesses Professional/Technical Mastery.
Innovates and Reapplies	Innovates Holistically, Creates, Improves Continually, Reapplies.
Leads	Envisions, Engages, Energizes, Enables, Executes.
Builds Diverse, Collaborative Relationships	Is Inclusive, Collaborates, Partners Externally, Builds Networks, Respects Others.
Grows Capability	Learns Continually, Anticipates Capability Gaps, Develops Others, Improves Systems.
In Touch	Listens to Understand, Connects, Focuses Externally, Turns Insights into Action, Is Aware, Possesses Self Awareness.
Embraces Change	Is Open to Change, Initiates Change, Is Flexible/Adaptable, Is Versatile.
Operates with Discipline	Focuses on Results, Is Accountable, Has a Scarcity Mindset, Plans and Follows Through, Focuses on Priorities.

Occupations

One question asked the participants to choose their job function (i.e., occupation) out of the following options: customer business development (i.e., sales), customer and market knowledge (i.e., market research), design, external relations (i.e., public relations or communications), finance and accounting, human resources, information and decision solutions (i.e., information technology), legal, marketing, product supply (i.e., manufacturing engineering), or research and development. Four occupations in particular were the most represented in this dataset: sales (*n* = 725), finance and accounting (*n* = 425), manufacturing engineering (*n* = 1066), and research and development (*n* = 868). Further details on the frequencies of occupations are found in Table 3.

Table 3

Frequencies of Occupations

Occupation	Frequency	Percent
Sales	725	17.5
Market Research	163	3.9
Design	61	1.5
External Relations	119	2.9
Finance and Accounting	425	10.3
Human Resources	128	3.1
Information Technology	243	5.9
Legal	30	.7
Marketing	309	7.5
Manufacturing Engineering	1066	25.8
Research and Development	868	21.0
Total	4137	100.0

Results

Upon examining the dataset for missing data, 430 cases were found to be missing personality items responses, with 87.7% of them missing either all or half of the responses. Given the large sample size of the current dataset (*n* = 4653), it was decided to keep only the participants who responded to all of the personality items (*n* = 4223) to be used for the next steps of analysis.

Composite variables were then created for the personality scales and job performance dimensions, and these variables were also converted into standardized z-score variables. Then, these standardized scores for personality and performance were sorted in ascending and descending order to check for outliers, with cases above 3.29 or below -3.29 on any of the composite variables considered an outlier. This check resulted in identifying 86 cases with outlying scores; these cases were deleted, resulting in a final dataset of 4137 participants.

An overall performance composite was then created based on the average of the scores of the nine performance dimensions. The descriptive statistics, correlations, and reliabilities of the main variables are reported in Table 4.

Table 4

Descriptive Statistics, Correlations, and Reliabilities of Personality and Performance

Variable	*M*	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. O	4.17	.40	(.73)													
2. A	4.19	.44	.41**	(.77)												
3. C	4.12	.44	.34**	.35**	(.70)											
4. E	3.83	.53	.51**	.38**	.27**	(.55)										
5. N	2.25	.52	-.42**	-.40**	-.25**	-.51**	(.60)									
6. TAD	3.58	.61	.05**	-0.02	.037*	.11**	-.12**	(.78)								
7. LM	3.57	.57	0.03	0.01	0.03	.12**	-.08**	.67**	(.69)							
8. IR	3.47	.59	.13**	0.03	-0.01	.15**	-.15**	.66**	.59**	(.80)						
9. Leads	3.39	.61	0.03	.09**	.06**	.16**	-.14**	.68**	.62**	.62**	(.80)					
10. BDCR	3.64	.60	0.02	.19**	.05**	.07**	-.09**	.46**	.51**	.50**	.60**	(.80)				
11.GC	3.53	.57	.05**	0.02	.08**	.09**	-.09**	.64**	.61**	.60**	.66**	.50**	(.72)			
12. IT	3.45	.58	0.03	.04**	0.03	.09**	-.09**	.64**	.62**	.63**	.67**	.62**	.62**	(.76)		
13. EC	3.54	.59	.09**	.05**	.03*	.12**	-.15**	.61**	.56**	.61**	.62**	.55**	.61**	.65**	(.75)	
14. OWD	3.68	.63	.02	-.02	.12**	.11**	-.09**	.69**	.58**	.54**	.64**	.41**	.64**	.61**	.57**	(.83)
15. PER	.02	.78	.06**	.06**	.06**	.14**	-.14**	.84**	.80**	.80**	.85**	.71**	.81**	.84**	.80**	.79**

Note. $^{*}p < .05$, $^{**}p < .01$. Cronbach's alpha noted on diagonal in parentheses. PER = Overall Performance, which was obtained by averaging z-scores of the job performance dimensions. O = Organization Openness, A = Organization Agreeableness, C = Organization Conscientiousness, E = Organization Extraversion, N = Organization Neuroticism, TAD = Thinks and Acts Decisively, LM = Leverages Mastery, IR = Innovates and Reapplies, BDCR = Builds Diverse, Collaborative Relationships, GC = Grows Capability, IT = In Touch, EC = Embraces Change, OWD = Operates with Discipline.

The study analyses are organized as follows. First, analyses for Hypotheses 1.1, 1.2, 1.3, and the Research Question that are based on all of the participants in the dataset are reported in Section 1 (Organizational Dataset). Then, analyses for Hypotheses 2.1, 2.2, and the Research Question that are based on participants from each of the four specific occupations of sales, finance and accounting, manufacturing engineering, and research and development, are reported in Section 2 (Occupational Datasets). This section includes 4 sub-sections with each dedicated to one of these occupations, and each sub-section will cover the results of Hypotheses 2.1, 2.2, and the Research Question for the participants in that occupation.

1. Organizational Dataset

Hypothesis 1.1

To examine Hypothesis 1.1 (multiple organization-based personality profiles will be identified), organization-based profiles (i.e., the whole organizational sample was used to conduct this analysis) were created using latent profile analysis (LPA) in Mplus. The technical specifications for conducting this analysis were based on literature recommendations on understanding and conducting LPA analysis (Asparouhov & Muthen, 2012; Geiser, 2012; Muthen & Muthen, 2012; Nylund, Asparouhov, & Muthen, 2017; Nylund-Gibson & Choi, 2018; Oberski, 2016; Tein, Coxe, & Cham, 2013; Tofighi & Enders, 2008; Woo, Jebb, Tay, & Parrigon, 2018).

Given that most of the profile results from previous research involved between three and five profiles, this analysis was conducted to test profile solutions between 2 and 10 to provide more information that would support the number of profiles to be chosen. Each LPA resulted in a set of model fit statistics and information criteria. A summary of these results is reported in Table 5.

Table 5

Model fit statistics for the 2- to 10-profile models.

No.	AIC	BIC	SABIC	Entropy	VLMR	*p*	LMR	*p*	BLRT	*p*
2	54010.95	54112.19	54061.35	0.69	-28656.17	0	3267.99	0	-28656.2	0
3	53082.40	53221.61	53151.71	0.72	-26989.47	0	922.09	0	-26989.5	0
4	**52870.46**	**53047.63**	**52958.66**	**0.67**	**-26519.20**	**0**	**219.55**	**0**	**-26519.2**	**0**
5	52750.65	52965.79	52857.76	0.66	-26407.23	0.09	129.22	**0.09**	-26407.2	0
6	52674.23	52927.34	52800.24	0.67	-26341.33	0.04	86.68	0.04	-26341.3	0
7	52614.13	52905.21	52759.04	0.65	-26297.12	0.39	70.69	0.39	-26297.1	0
8	52554.38	52883.42	52718.19	0.66	-26261.07	0.66	70.34	0.66	-26261.1	0
9	52493.39	52860.40	52676.10	0.67	-26225.19	0.02	71.55	0.02	-26225.2	0
10	52447.96	52852.94	52649.57	0.68	-26188.70	0.17	56.31	0.18	-26188.7	0

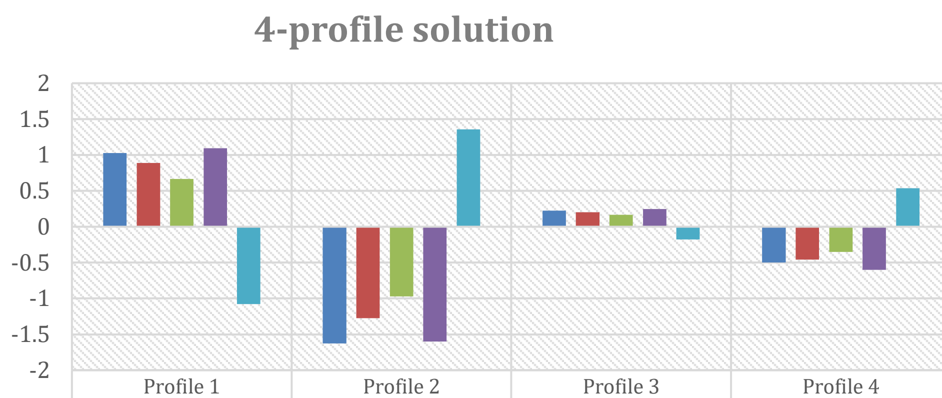
There does not appear to be consensus on one recommended way to decide on the number of profiles. Several pieces of information can help users make a judgement regarding the right number of latent profiles in a sample. For instance, Nylund et al. (2017) emphasized the importance of the Bootstrapped Likelihood Ratio Test (BLRT) and the Bayesian Information Criterion (BIC), while Tofighi and Enders (2008) highlighted the criteria of Sample-Size Adjusted BIC (SABIC) and Lo-Mendell-Rubin adjusted LRT test (LMR). These recommendations typically suggest using these criteria in addition to taking into consideration the interpretability of the profile solutions.

In examining the analysis results shown in Table 5, the first examined recommended criterion is the BIC. The recommendation for this criterion is to select the number of profiles that provides the lowest BIC value. In some situations, the BIC may show declining values until a point where it starts to increase again, but in the current LPA the BIC value kept declining with no clear stopping point. Hence, this factor did not help in choosing the right number of profiles. Second, the BLRT factor was examined. This test provides the significance of a proposed number of profiles (K) in comparison with a model that contains 1 fewer profile (K-1). The recommendation for this factor is to choose the number of profiles based on the point where the test *p*-value becomes non-significant, indicating that the last significant result refers to the right number of latent profiles. However, in this LPA the *p*-values of BLRT were all significant for models 2 to 10. This supports the notion that a model with 2 profiles is preferable to a model with 1 profile, based on the significance value provided for the 2-profile solution's BLRT. However, this criterion did not help us decide the right number of profiles in the current LPA.

Third, the SABIC was examined. The recommendation for this factor is to choose the profile solution based on the lowest value of SABIC. However, in the current LPA, the SABIC values declined across all the investigated number of profiles. Fourth, the LMR was examined. This test also provides the significance of a model with a specific number of profiles (K) in comparison with a model that includes K-1 profiles. The recommendation for this factor is to identify the profile solution at which the *p*-value becomes non-significant, indicating that the last significant result refers to the right number of latent profiles. In the current analysis, this distinction point occurred for the 5-profile solution ($p > .05$), indicating that a model with a 4-profile solution may be appropriate.

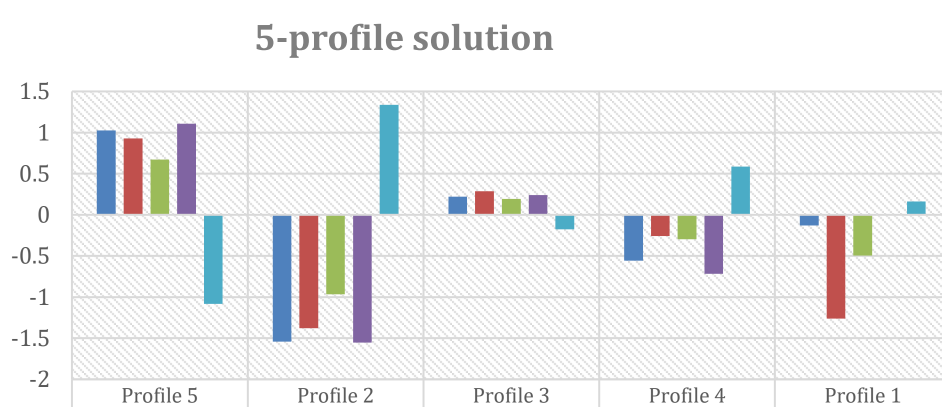
Finally, the fifth factor of interpretability was taken into consideration. To examine this aspect, I made a graph that shows the mean scores in terms of the Big Five personality factors for the 4-profile solution, 5-profile solution, and the 6-profile solution, as shown in Figures 1-3. As can be seen, the pattern of the four profiles identified in Figure 1 was replicated in the 5-profile solution and the 6-profile solution.

In Figure 2, the identified profiles represent an approximate replication for the 4 profiles identified earlier, with the addition of one profile. Profile 1 in Figure 2 (the additional profile) is quite similar to profile 4 in the same figure. Accordingly, the additional profile did not seem to add a distinctive additional pattern, suggesting support for the 4-profile solution. Finally, a closer look at the 6-profile solution in Figure 3 indicates the approximate replication of the 4-profile solution in addition to two extra profiles. These two additional profiles do not seem to replicate findings from previous studies. In addition, they seem to be the result of a split of profile 4 in the 5-profile solution (25.2%) into profiles 1, 4, and 6 in the 6-profile solution (3.9%, 16.6%, and 4.6%, respectively), and thus involve an emerging pattern of smaller profiles. These considerations suggest that the 4-profile solution may be reasonable and parsimonious in terms of representing the current dataset.



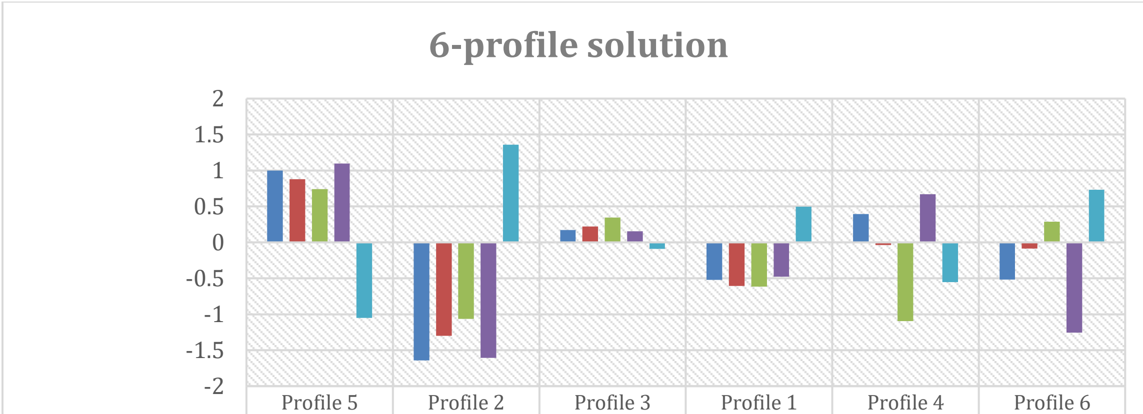
	Profile 1	Profile 2	Profile 3	Profile 4
Openness	1.025	-1.626	0.222	-0.497
Agreeableness	0.887	-1.273	0.204	-0.46
Conscientiousness	0.666	-0.971	0.165	-0.35
Extraversion	1.096	-1.602	0.245	-0.6
Neuroticism	-1.078	1.357	-0.179	0.536

Figure 1. Four latent personality profiles solution by mean Big Five scores.



	Profile 5	Profile 2	Profile 3	Profile 4	Profile 1
Openness	1.026	-1.543	0.221	-0.557	-0.128
Agreeableness	0.927	-1.378	0.285	-0.258	-1.262
Conscientiousness	0.67	-0.967	0.193	-0.296	-0.496
Extraversion	1.106	-1.554	0.24	-0.719	-0.001
Neuroticism	-1.082	1.338	-0.176	0.586	0.161

Figure 2. Five latent personality profiles solution by mean Big Five scores.



	Profile 5	Profile 2	Profile 3	Profile 1	Profile 4	Profile 6
Openness	0.999	-1.642	0.172	-0.521	0.393	-0.515
Agreeableness	0.877	-1.301	0.221	-0.604	-0.036	-0.084
Conscientiousness	0.739	-1.063	0.344	-0.614	-1.097	0.289
Extraversion	1.098	-1.607	0.155	-0.479	0.67	-1.257
Neuroticism	-1.052	1.36	-0.09	0.497	-0.552	0.731

Figure 3. Six latent personality profiles solution by mean Big Five scores.

Furthermore, additional pieces of information that were provided in the LPA results for the 4-profile solution indicate the adequacy of this solution. The counts and proportions of the four profiles show that each profile represented more than 5% of the dataset, in line with the recommendations from Nylund et al. (2007; see Table 6).

Table 6

Profile Counts and Proportions

Profile	Count	Percentage
1	646	15.61%
2	220	5.32%
3	1980	47.86%
4	1291	31.21%

Also, the classification probabilities for the most likely latent profile membership by latent profile indicates high likelihoods of participants being classified to an appropriate profile, with probabilities ranging from .767 to .834, as shown in Table 7.

Table 7

Classification probabilities for the most likely latent profile membership (column) by latent profile (row).

	1	2	3	4
1	**0.767**	0.000	0.233	0.000
2	0.000	**0.774**	0.000	0.225
3	0.058	0.000	**0.834**	0.108
4	0.000	0.027	0.187	**0.786**

Accordingly, it was decided that the 4-profile solution is appropriate for this analysis, and profile membership for each participant was added to the dataset. This took the form of a categorical variable showing the most likely classification, in addition to four continuous variables that show the probabilities of belonging to the four profiles for each of the participants. Based on these findings, Hypothesis 1.1 (multiple organization-based personality profiles will be identified) was supported.

For ease of reference and interpretability for the identified profiles, each profile was labeled. Figure 1 shows profile 1 with below average neuroticism and above average openness, agreeableness, conscientiousness, and extraversion. This profile is similar to the resilient profile (Asendorpf et al., 2001; Herzberg & Roth, 2006; Kinnunen et al., 2012; Zhang et al. 2015) and the well-adjusted profile (Ferguson & Hull, 2018; Merz & Roesch, 2011) previously found in the literature. However, in the current study, a judgement was made to call this profile “adaptable” as will be explained later in the discussion section. As for profile 2, this profile shows above average neuroticism and below average openness, agreeableness, conscientiousness, and extraversion. This profile is similar to the rigid profile (Zhang et al., 2015) and the non-desirable profile (Rammstedt, Riemann, Angleitner, & Borkenau, 2004). In the current study it was decided to name it “rigid.”

As for profile 3, this profile shows slightly below average neuroticism and slightly above average openness, agreeableness, conscientiousness, and extraversion. This profile is similar to the confident profile found previously (Zhang et al., 2015), and it was decided to keep the same name. Finally, profile 4 shows slightly above average neuroticism and slightly below average openness, agreeableness, conscientiousness, and extraversion. This profile is similar to the ordinary profile found previously (Zhang et al., 2015). However, in the current study it was decided to name it "nervous," as will be explained later in the discussion section.

Hypothesis 1.2

Next, in examining Hypothesis 1.2 (organization-based personality profiles will have a contribution above and beyond personality traits in predicting organization-wide job performance), regression analyses were conducted using overall job performance and the individual job performance dimensions as separate dependent variables. First, multiple linear regression analyses were conducted to explore the predictive ability of personality traits, personality profiles (categorical), and personality profiles (continuous) for job performance. Second, hierarchical regression analyses were conducted to examine the contribution of personality profiles above and beyond personality traits.

The initial multiple linear regression analyses show the results for personality traits (Table 8), personality profiles (categorical; Table 9), and personality profiles (continuous; Table 10) in predicting overall job performance. Personality traits were significant predictors of overall job performance (R = .16, R^2 = .027, F(5,4131) = 22.830, p < .001). Specifically, the significant trait predictors are openness (b = -.037, p < .05), extraversion (b = .090, p < .001), and neuroticism (b = -.077, p < .001).

Table 8

Summary of Regression Analysis for Overall Performance by Personality Traits

	R	R^2	*SE* of the Estimate	b	*SE*	B
Model 1	$.164^{***}$	.027	.773			
O				$-.037^{*}$	.016	-.045
A				-.014	.015	-.017
C				.020	.014	.025
E				$.090^{***}$	.016	.113
N				$-.077^{***}$	.015	-.096

$^{*}p < .05$, $^{***}p < .001$. O = Organization Openness, A = Organization Agreeableness, C = Organization Conscientiousness, E = Organization Extraversion, N = Organization Neuroticism.

Personality profiles (categorical), as represented by dummy coded variables in Table 9, were also significant predictors of overall job performance ($R = .12$, $R^2 = .015$, $F(3,4133) = 20.714$, $p < .001$). The regression coefficient for profile 1 dummy-coded variable ($b = .194$, $p < .001$) indicates that membership in profile 1 (i.e., adaptable) is associated with an increase in job performance. The regression coefficient for profile 3 (i.e., confident) is also positive ($b = .152$, $p < .001$). Finally, membership in profile 2 (i.e., rigid) is associated with a decrease in job performance ($b = -.150$, $p < .001$).

Table 9

Summary of Regression Analysis for Overall Performance by Profiles (Categorical)

	R	R^2	*SE* of the Estimate	*b*	*SE*	*B*
Model 1	.122	.015	.777			
Profile 1 dummy variable				$.194^{***}$	.037	.090
Profile 2 dummy variable				$-.150^{**}$	.057	-.043
Profile 3 dummy variable				$.152^{***}$	.028	.097

$^{**}p < .01$, $^{***}p < .001$.

Personality profiles (continuous), as represented by profile probability variables in Table 10, were also found to be significant predictors of overall job performance (R = .14, R^2 = .018, F(3,4133) = 25.847, p < .001). The probability of profile 2 (i.e., rigid) membership was associated with a decrease in performance (b = -.406, p < .001), and the probability of profile 4 (i.e., nervous) membership was also associated with a decrease in performance (b = -.202, p < .001).

Table 10

Summary of Regression Analysis for Overall Performance by Profiles (Continuous)

	R	R^2	*SE* of the Estimate	*b*	*SE*	*B*
Model 1	.136***	.018	.776			
CPROB1				.011	.047	.004
CPROB2				-.406***	.063	-.102
CPROB4				-.202***	.040	-.091

***$p < .001$. *N.B.* CPROB3 was automatically excluded from the model. The value of its collinearity statistics tolerance is 1.94E-6. CPROB1 = probability of profile 1 membership, CPROB2 = probability of profile 2 membership, CPROB4 = probability of profile 4 membership.

Funder and Ozer (2019) have provided arguments on two important aspects of interpreting the results of psychological research: (a) it is more appropriate to focus on the effect sizes rather than the squared value of effect sizes, and (b) based on literature they recommend considering an effect size of .05 to be very small, .10 to be small, .20 to be medium, and .30 to be large. Accordingly, it seems that the three sets of personality predictors (traits, categorical profiles, and continuous profiles) show validity values in the range between small and medium effect sizes (R = .16, .12, .14, respectively).

A one-way ANOVA was further conducted to provide another way to look at and explain the effect of profile membership on job performance levels. (Table 11). This analysis showed significant differences in the levels of overall job performance based on profile membership (F (3,4133) = 20.714, $p < .001$), and further information can be seen in Appendix A. Table 12 shows the means of performance across the four profiles. As for mean performance levels, it is shown that performance is ranked in a descending order from adaptable, to confident, to nervous, to rigid.

Table 11

One-way ANOVA Results for Profiles using Overall Performance as the Criterion

Source	Sum of Squares	*df*	Mean Square	*F*	Sig.	Partial Eta Squared
Between Groups	37.594	3	12.531	20.714	.000	.015
Within Groups	2500.338	4133	.605			
Total	2537.932	4136				

Table 12

Means of Overall Performance Across Profiles

Profile	Mean	SD
Adaptable	.120	.785
Rigid	-.224	.802
Confident	.079	.781
Nervous	-.073	.765

Next, the incremental validity of both categorical profiles (Table 13) and continuous profiles (Table 14) in predicting overall job performance was examined using a hierarchical regression analysis where traits are added in the first step, followed by the profiles being tested in the second step. In Table 13, the first step included traits (R = .16, F(5,4131) = 22.830, p < .001) and the second step included the categorical profiles. The change in prediction was found to be non-significant (ΔR = .005, ΔF (3, 4128) = 2.497, p > .05). Therefore, categorical profiles did not show incremental validity in predicting overall job performance above and beyond traits.

Table 13

Summary of Hierarchical Regression Analysis for Overall Performance

	R	R^2	*SE* of the Estimate	R^2 change	*b*	*SE*	*B*
Model 1	.164***	.027	.773	. .027***			
O					-.037*	.016	-.045
A					-.014	.015	-.017
C					.020	.014	.025
E					.090***	.016	.113
N					-.077***	.015	-.096
Model 2	.169***	.029	.773	.002			
O					-.030	.019	-.037
A					-.009	.017	-.011
C					.023	.014	.028
E					.097***	.019	.122
N					-.085***	.017	-.107
Profile 1 dummy variable					-.103	.085	-.048
Profile 2 dummy variable					-.009	.071	-.002
Profile 3 dummy variable					.010	.046	.006

*p < .05, ***p < .001. O = Organization Openness, A = Organization Agreeableness, C = Organization Conscientiousness, E = Organization Extraversion, N = Organization Neuroticism.

In Table 14, the first step again included traits and the second step included continuous profiles. The change in prediction was found to be significant (ΔR = .009, ΔF (3, 4128) = 4.351, p < .01). Therefore, continuous profiles showed small incremental validity in predicting overall job performance above and beyond traits.

Table 14

Summary of Hierarchical Regression Analysis for Overall Performance

	R	R^2	*SE* of the Estimate	R^2 change	*b*	*SE*	*B*
Model 1	.164***	.027	.773	. .027***			
O					-.037*	.016	-.045
A					-.014	.015	-.017
C					.020	.014	.025
E					.090***	.016	.113
N					-.077**	.015	-.096
Model 2	.173***	.030	.772	.003**			
O					-.011	.035	-.013
A					.005	.026	.006
C					.031	.019	.039
E					.119**	.037	.150
N					-.104***	.030	-.131
CPROB1					-.306	.253	-.119
CPROB2					.027	.146	.007
CPROB3					-.050	.128	-.023

*p < .05, **p < .01, ***p < .001. O = Organization Openness, A = Organization Agreeableness, C = Organization Conscientiousness, E = Organization Extraversion, N = Organization Neuroticism.

To examine the incremental validity of profiles in predicting individual job performance dimensions, initial multiple linear regression analyses were conducted to show the criterion-related validity of personality traits (Table 15), personality profiles (categorical; Table 16), and personality profiles (continuous; Table 17) in predicting each of the job performance dimensions. The three sets of personality predictors were found to be significant in predicting each job performance dimension ($p < .001$). Note that the validity values were highest for traits, followed by continuous profiles, and then categorical profiles.

Table 15

Summary of Regression Analysis for Individual Performance Dimensions

IV: Traits		IV: Profiles (Categorical)		IV: Profiles (Continuous)	
R	R^2	*R*	R^2	*R*	R^2
DV: Thinks and Acts Decisively					
.159***	.025	.090***	.008	.100***	.010
DV: Leverages Mastery					
.131***	.017	.086***	.007	.098***	.010
DV: Innovates and Reapplies					
.194***	.038	.130***	.017	.144***	.021
DV: Leads					
.188***	.035	.121***	.015	.134***	.018
DV: Builds Diverse, Collaborative Relationships					
.210***	.044	.100***	.010	.113***	.013
DV: Grows Capability					
.123***	.015	.092***	.008	.101***	.010
DV: In Touch					
.106***	.011	.073***	.005	.086***	.007
DV: Embraces Change					
.157***	.025	.118***	.014	.129***	.017
DV: Operates with Discipline					
.187***	.035	.079***	.006	.086***	.007

***$p < .001$.

To test for the incremental validity of categorical profiles and continuous profiles, hierarchical regression analyses were conducted where the first step included traits and the second step included the profiles for each of the nine job performance dimensions. Only 7 analyses out of these 18 were found to be significant. For ease of reference, a summary of the significant analyses is reported in Table 16, and Appendix A shows further information on all of the analyses including the significant and non-significant results. As shown in Table 16, continuous profiles showed small incremental validity above and beyond traits for six performance dimensions (i.e., Thinks and Acts Decisively, Leverages Mastery, Innovates and Reapplies, Grows Capability, In Touch, Embraces Change), and categorical profiles showed small incremental validity over traits for one performance dimension (i.e., Leverages Mastery).

Table 16

Summary of Hierarchical Regression Analysis for Individual Performance Dimensions with Significant Results

Model	*R*	R^2	R^2 change
DV: Thinks and Acts Decisively			
1. Traits	.159***	.025	.025***
2. Profiles (Continuous)	.169***	.029	.003**
DV: Leverages Mastery			
1. Traits	.131***	.017	.017***
2. Profiles (Categorical)	.141***	.020	.003**
DV: Leverages Mastery			
1. Traits	.131***	.017	.017***
2. Profiles (Continuous)	.146***	.021	.004**
DV: Innovates and Reapplies			
1. Traits	.194***	.038	.038***
2. Profiles (Continuous)	.199***	.040	.002*
DV: Grows Capability			
1. Traits	.123***	.015	.015***
2. Profiles (Continuous)	.132***	.017	.002*
DV: In Touch			
1. Traits	.106***	.011	.011***
2. Profiles (Continuous)	.115***	.013	.002*

DV: Embraces Change			
1. Traits	$.157^{***}$	.025	$.025^{***}$
2. Profiles (Continuous)	$.165^{***}$	.027	$.002^{*}$

$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

Based on the results of the hierarchical regression analyses in predicting overall job performance and the job performance dimensions, Hypothesis 1.2 (organization-based personality profiles will have a contribution above and beyond personality traits in predicting organization-wide job performance) was partially supported.

Hypothesis 1.3

Next, to examine Hypothesis 1.3 (occupations will moderate the relationship between organization-based personality profiles and job performance), a two-way ANOVA was conducted using job performance as the criterion, and profiles and occupations as factors. The test of most interest is the interaction of these factors, indicating whether the effect of profiles on job performance is affected by occupational membership. First, a two-way ANOVA was conducted with overall job performance as the criterion (Table 17), and the results showed that the interaction between profiles and occupations was not significant (F (30,4093) = 1.187, $p > .05$).

Table 17

Two-way ANOVA Results for Profiles and Occupations using Overall Performance as the Criterion

Source	Sum of Squares	*df*	Mean Square	*F*	Partial Eta Squared
Between Groups					
Profiles	11.632	3	3.877	6.461^{***}	.005
Occupation	15.356	10	1.536	2.559^{**}	.006
Profiles*Occupation	21.369	30	.712	1.187	.009
Within Groups	2456.382	4093	.600		
Total	2537.932	4136			

$^{**}p < .01$, $^{***}p < .001$.

Then, the same analysis was repeated for each of the nine performance dimensions. All of the analyses showed non-significant results for the interaction between profiles and occupations, except for the dimension of Thinks and Acts Decisively (Table 18) where the interaction was found to be significant (F (30,4093) = 1.496, $p < .05$). The post-hoc test and the plot for the interaction effect can be seen in Appendix B. Also, for ease of reference, the results of all the two-way ANOVAs are reported in Appendix C including the significant and non-significant results.

Table 18

Two-way ANOVA Results for Profiles and Occupations using Thinks and Acts Decisively as the Criterion

Source	Sum of Squares	*df*	Mean Square	*F*	Partial Eta Squared
Between Groups					
Profiles	4.373	3	1.458	1.571	.001
Occupation	32.687	10	3.269	3.522^{***}	.009
Profiles*Occupation	41.636	30	1.388	1.496^{*}	.011
Within Groups	3798.158	4093	.928		
Total	3923.538	4136			

$^{*}p < .05$, $^{***}p < .001$.

Based on these ANOVA results, Hypothesis 1.3 (occupations will moderate the relationship between organization-based personality profiles and job performance) was mostly unsupported in light of having one significant moderation result out of the ten analyses conducted.

Research Question

Finally, the Research Question (what is the distribution of personality profiles for the top 10% of performers in the organization and within occupations) was examined. Figure 4 below shows the four personality profiles identified with labels for ease of reference.

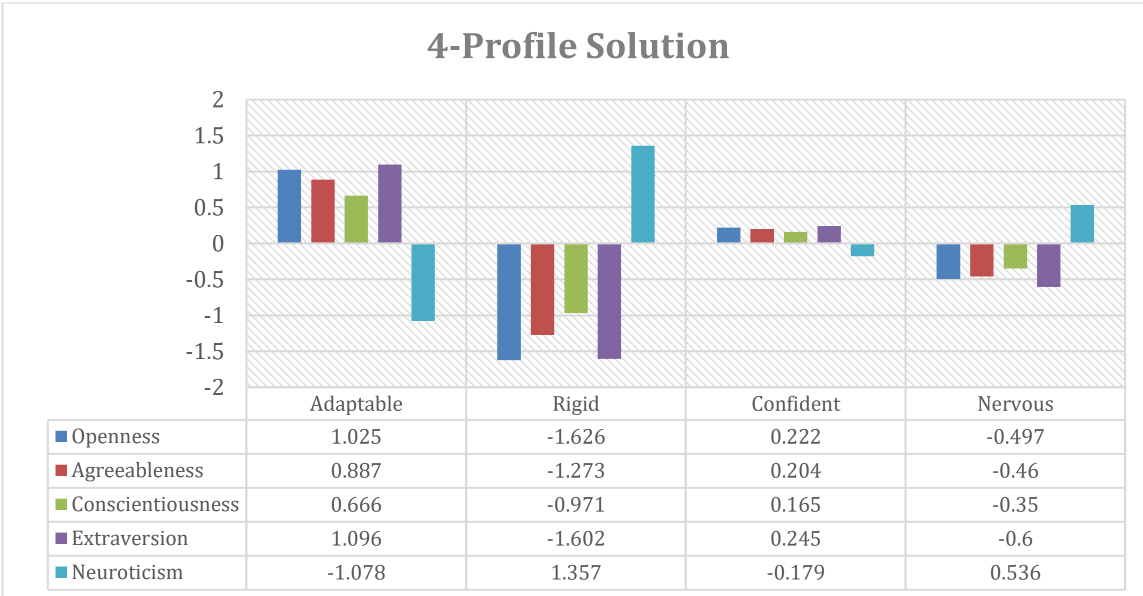


Figure 4. Four latent personality profiles solution by mean Big Five scores (Labeled).

Also, Table 19 shows the frequencies of the organization-based profiles within the organization. The frequencies indicate that confident and nervous were the most common, and rigid was the least common.

Table 19

Frequencies of Profiles Within the Organization

Organization Based Profiles	Frequency	Percentage
Adaptable	646	15.61
Rigid	220	5.32
Confident	1980	47.86
Nervous	1291	31.21
Total	4137	100.00

An analysis of only the top 10% of performers (*n* = 414) showed the profile frequencies reported in Table 20. The confident profile was found to be the most common in the subset of the top 10% of performers (52.7%) which is higher than their representation in the overall sample (47.86%), followed by the nervous profile (24.9%) which is lower than their representation in the overall sample (31.21%), the adaptable profile (20.0%) which is higher than their representation in the overall sample (15.61%), and the rigid profile (2.4%) which is lower than their representation in the overall sample (5.32%).

Table 20

Frequencies of Profiles Within the Top 10% of Performers

	Frequency	Percent
Adaptable	83	20.0
Rigid	10	2.4
Confident	218	52.7
Nervous	103	24.9
Total	414	100.0

2. Occupational Datasets

Subsets of data were created so that each subset included only the participants from a specific occupation (i.e., sales, finance and accounting, manufacturing engineering, or research and development). Variables indicating organization-based personality profiles identified in the previous section (both categorical and continuous variables) were kept during the extraction of these subsets of data to enable us to compare between organization-based profiles (previously identified) and occupation-based profiles (to be identified) within each subset of data.

a. Sales

Hypothesis 2.1

To examine Hypothesis 2.1 (multiple occupation-based personality profiles will be identified), LPA was conducted. The profile solutions 2 to 6 were examined as results provided indications that models with more profiles are not needed to identify the appropriate number of latent profiles. These LPAs resulted in a set of model fit statistics and information criteria. A summary of these results is reported in Table 21.

Table 21

Model fit statistics for the 2- to 6-profile models.

No.	AIC	BIC	SABIC	Entropy	VLMR	*p*	LMR	*p*	BLRT	*p*
2	9384.38	9457.76	9406.96	0.70	-4997.33	0	626.44	0	-4997.33	0
3	9201.11	9302.00	9232.14	0.74	-4676.19	0.001	190.46	0.001	-4676.19	0
4	**9163.09**	**9291.50**	**9202.59**	**0.68**	**-4578.55**	**0.006**	**48.78**	**0.007**	**-4578.55**	**0**
5	9138.82	**9294.75**	9186.79	0.69	-4553.54	0.264	35.38	**0.272**	-4553.54	0
6	9121.77	9305.22	9178.21	0.71	-4535.41	0.168	28.33	0.175	-4535.41	0

The results in Table 21 show that the first guiding factor (BIC) had declining values until profile solution 5, where it started to increase again, which supports the selection of the 4-profile solution. The second guiding factor (BLRT) showed significant *p*-values across all examined profile solutions; therefore, it was deemed not helpful in supporting a specific profile solution. The third guiding factor (SABIC) showed declining values across all examined profile solutions; therefore, it was also deemed not helpful in supporting a specific profile solution. The fourth guiding factor (LMR) showed significant *p*-values until it reached the 5-profile solution where it turned non-significant, indicating that the model with 4-profiles may be preferable. The fifth guiding factor was interpretability, and the graph shown in Figure 5 below shows a replicable pattern of the four organization-based profiles identified previously, which provides easily interpretable differences between the four profiles. Accordingly, it was decided that the 4-profile solution is appropriate for this analysis.

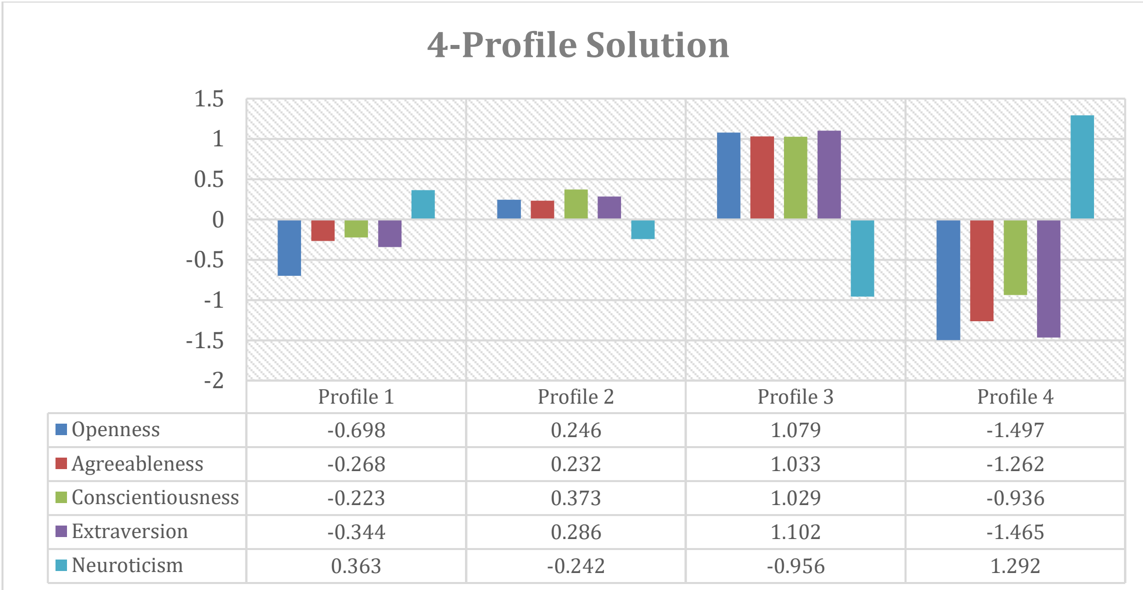


Figure 5. Four latent occupation-based personality profiles solution by mean Big Five scores for Sales.

Furthermore, additional pieces of information that were provided in the LPA results for the 4-profile solution indicate the adequacy of this solution. The counts and proportions of the four profiles shows each profile represents more than 5% of the dataset, in line with the recommendation from Nylund et al. (2007), as shown in Table 22.

Table 22

Profile Counts and Proportions

Profile	Count	Percentage
1	205	28.28%
2	338	46.62%
3	138	19.03%
4	44	6.07%

Also, the classification probabilities for the most likely latent profile membership by latent profile indicates high likelihoods of participants being classified to an appropriate profile, with probabilities ranging from .777 to .834, as shown in Table 23. Based on these results, Hypothesis 2.1 (multiple occupation-based personality profiles will be identified) was supported.

Table 23

Classification probabilities for the most likely latent profile membership (column) by latent profile (row).

	1	2	3	4
1	**0.777**	0.203	0.000	0.020
2	0.096	**0.834**	0.070	0.000
3	0.000	0.185	**0.814**	0.000
4	0.166	0.000	0.000	**0.834**

For ease of reference and interpretability, the profiles were again labeled. Upon visually examining the graph representing the four profiles (Figure 5), it was clear that these are very similar to the four organization-based profiles identified in Section 1. Therefore, a judgement was made to give them the same labels, where profile 1 is “nervous”, profile 2 is “confident”, profile 3 is “adaptable”, and profile 4 is “rigid.”

Hypothesis 2.2

To examine Hypothesis 2.2 (occupation-based personality profiles will have a contribution above and beyond both personality traits and organization-based personality profiles in predicting job performance), regression analyses were conducted using overall job performance and the individual job performance dimensions as separate dependent variables. Given that the organizational-based profiles in Section 1 were found to have higher validity in the form of continuous variables rather than categorical variables, only the set of continuous variables will be used to represent the contribution of organization-based profiles in these analyses.

First, multiple linear regression analyses were conducted to explore the predictive ability of personality traits, organization-based personality profiles, and occupation-based personality profiles (categorical and continuous) for job performance. Second, hierarchical regression analyses were conducted to examine the contribution of occupation-based personality profiles above and beyond personality traits and organization-based personality profiles.

The initial multiple linear regression analyses show the results for personality traits, organization-based personality profiles, and occupation-based personality profiles (categorical and continuous) in predicting overall job performance (see the summary in Table 24; see further information in Appendix D). The results provided in Table 24 show higher validity values for personality traits, followed by the three tested sets of personality profiles as predictors of overall job performance. Within these three sets of profiles, it can be observed that validity was slightly higher for organization-based profiles, followed by the occupation-based profiles in their continuous form and then the occupation-based profiles in their categorical form.

Table 24

Summary of Regression Analyses for Overall Performance

IV: Traits		IV: Org-Based Profiles		IV: Occ-Based Profiles (Categorical)		IV: Occ-Based Profiles (Continuous)	
R	R^2	R	R^2	R	R^2	R	R^2
$.180^{***}$	.032	$.104^{*}$	.011	.089	.008	.096	.009

$^{*}p < .05$, $^{***}p < .001$.

A one-way ANOVA was further conducted to provide another way to look at and explain the effect of profile membership on job performance levels (Table 25). This analysis showed significant differences in the levels of overall job performance based on profile membership (F (3,721) = 1.929, p < .01), and further information can be seen in Appendix D. Table 26 shows the means of performance across the four profiles. As for mean performance levels, it is shown that performance is ranked in descending order from adaptable, to nervous, to confident, to rigid.

Table 25

One-way ANOVA Results for Profiles using Overall Performance as the Criterion

Source	Sum of Squares	*df*	Mean Square	*F*	Sig.	Partial Eta Squared
Between Groups	4.004	3	1.335	1.929	.123	.008
Within Groups	498.862	721	.692			
Total	502.866	724				

Table 26

Means of Overall Performance Across Profiles

Profile	Mean	SD
Nervous	-.052	.862
Confident	-.055	.773
Adaptable	-.034	.914
Rigid	-.359	.854

The incremental validity of both occupation-based categorical and continuous profiles in predicting overall job performance was then examined using a hierarchical regression analysis where traits are added in the first step, organization-based profiles are added in the second step, and occupation-based profiles are added in the third step. Table 27 shows a summary of the analyses where occupation-based profiles did not provide significant incremental validity over both traits and organization-based profiles. This table also shows results for analyses involving organization-based profiles added in the final step. Results indicated the organization-based profiles did not provide significant incremental validity over both traits and occupation-based profiles.

Table 27

Summary of Hierarchical Regression Analysis for Overall Performance with Significant Results

Model	R	R^2	R^2 change
1. Traits	.180***	.032	.032***
2. Org-Based Profiles	.192**	.037	.005
3. Occ-Based Profiles (Categorical)	.205**	.042	.005
1. Traits	.180***	.032	.032***
2. Org-Based Profiles	.192**	.037	.005
3. Occ-Based Profiles (Continuous)	.207**	.043	.006
1. Traits	.180***	.032	.032***
2. Occ-Based Profiles (Categorical)	.195**	.038	.005
3. Org-Based Profiles	.205**	.042	.004
1. Traits	.180***	.032	.032***
2. Occ-Based Profiles (Continuous)	.200***	.040	.008
3. Org-Based Profiles	.207**	.043	.003

**$p < .01$, ***$p < .001$.

To examine the incremental validity of profiles in predicting individual job performance dimensions, initial multiple linear regression analyses were conducted to show the criterion-related validity of occupation-based profiles (categorical and continuous) in predicting each of the job performance dimensions as shown in Table 28. The two sets of personality profiles were found to be mostly non-significant in predicting each job performance dimension ($p > .05$), with the exception of continuous profiles predicting Leads ($p < .05$) and categorical and continuous profiles predicting Embraces Change ($p < .05$, $p < .01$, respectively). Note also that the validity values were mostly higher for the continuous profiles than the categorical profiles.

Table 28

Summary of Regression Analysis for Individual Performance Dimensions

IV: Occ-Based Profiles (Categorical)		IV: Occ-Based Profiles (Continuous)	
R	R^2	*R*	R^2
DV: Thinks and Acts Decisively			
.066	.004	.075	.006
DV: Leverages Mastery			
.096	.009	.104	.011
DV: Innovates and Reapplies			
.102	.010	.101	.010
DV: Leads			
.104	.011	$.112^{*}$	.012
DV: Builds Diverse, Collaborative Relationships			
.073	.005	.086	.007
DV: Grows Capability			
.071	.005	.083	.007
DV: In Touch			
.045	.002	.050	.003
DV: Embraces Change			
$.122^{*}$	.015	$.129^{**}$	.017
DV: Operates with Discipline			
.091	.008	.088	.008

$^{*}p < .05$, $^{**}p < .01$.

To test for the incremental validity of occupation-based categorical and continuous profiles in predicting individual performance dimensions, hierarchical regression analyses were conducted where the first step included traits, the second step included organization-based profiles, and the third step included occupation-based profiles for each of the nine job performance dimensions. Only 1 analysis out of these 18 was found to be significant, involving the dimension of Leverages Mastery as seen in Table 29. This table also shows results for analyses involving organization-based profiles added in the final step. Further information on all of the hierarchical regression analyses, including the significant and non-significant results, can be seen in Appendix D.

Table 29

Summary of Hierarchical Regression Analysis for Individual Performance Dimensions with Significant Results

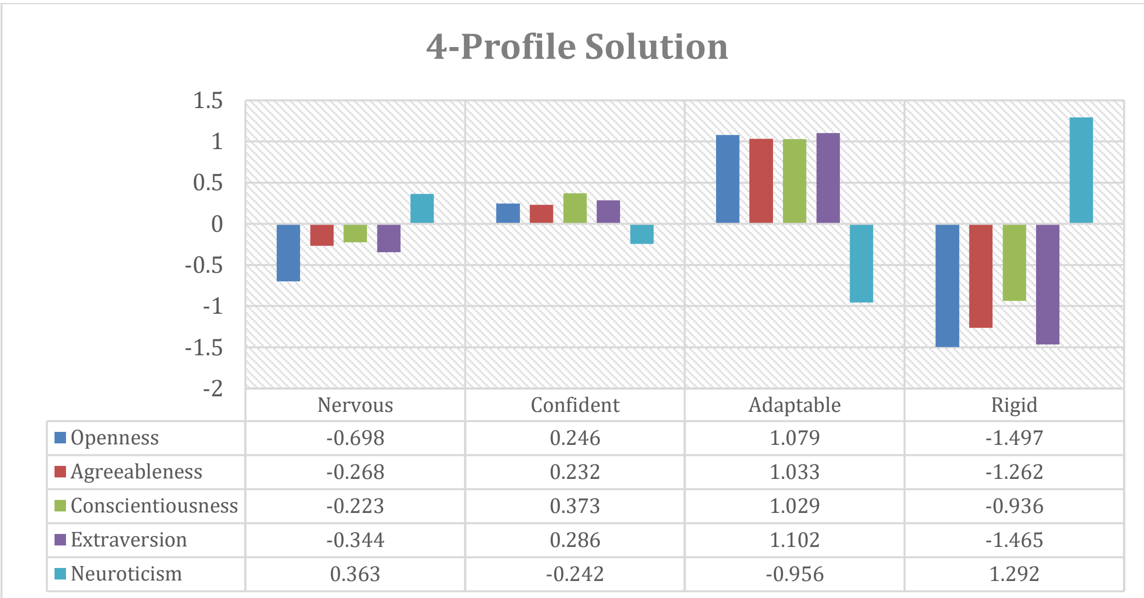
Model	R	R^2	R^2 change
	DV: Leverages Mastery		
1. Traits	.130*	.017	.017*
2. Org-Based Profiles	.167**	.028	.011*
3. Occ-Based Profiles (Categorical)	.190**	.036	.008
	DV: Leverages Mastery		
1. Traits	.130*	.017	.017*
2. Org-Based Profiles	.167**	.028	.011*
3. Occ-Based Profiles (Continuous)	.196**	.039	.011*
	DV: Leverages Mastery		
1. Traits	.130*	.017	.017*
2. Occ-Based Profiles (Categorical)	.173**	.030	.013*
3. Org-Based Profiles	.190**	.036	.006
	DV: Leverages Mastery		
1. Traits	.130*	.017	.017*
2. Occ-Based Profiles (Continuous)	.188**	.035	.018**
3. Org-Based Profiles	.196**	.039	.003

$^*p < .05$, $^{**}p < .01$.

Based on the results of the hierarchical regression analyses in predicting overall job performance and the individual job performance dimensions, Hypothesis 2.2 (occupation-based personality profiles will have a contribution above and beyond both personality traits and organization-based personality profiles in predicting job performance) was mostly unsupported.

Research Question

Finally, the Research Question (what is the distribution of personality profiles for the top 10% of performers in the organization and within occupations) was examined. Figure 6 below shows the four personality profiles identified with labels for ease of reference.



	Nervous	Confident	Adaptable	Rigid
Openness	-0.698	0.246	1.079	-1.497
Agreeableness	-0.268	0.232	1.033	-1.262
Conscientiousness	-0.223	0.373	1.029	-0.936
Extraversion	-0.344	0.286	1.102	-1.465
Neuroticism	0.363	-0.242	-0.956	1.292

Figure 6. Four latent occupation-based personality profiles solution by mean Big Five scores for Sales (Labeled).

Also, Table 30 shows the frequencies of the organization-based and occupation-based profiles with the sales occupation. The frequencies indicate that confident and nervous were the most common, and rigid was the least common.

Table 30

Frequencies of Profiles Within Sales

Occupation-Based Profiles	Frequency	Organization Based Profiles	Frequency
Nervous	205 (28.3%)	Adaptable	142 (19.6%)
Confident	338 (46.6%)	Rigid	38 (5.2%)
Adaptable	138 (19%)	Confident	358 (49.4%)
Rigid	44 (6.1%)	Nervous	187 (25.8%)
Total	725	Total	725

An analysis of only the top 10% of performers (n = 73) showed the profile frequencies reported in Table 31. The confident profile was found to be the most common in the subset of the top 10% of performers (38.4%) which is lower than their representation in the overall sample (46.6%), followed by the nervous profile (30.1%) which is higher than their representation in the overall sample (28.3%), the adaptable profile (28.8%) which is higher than their representation in the overall sample (19%), and the rigid profile (2.7%) which is lower than their representation in the overall sample (6.1%).

Table 31

Frequencies of Profiles Within the Top 10% of Performers

	Frequency	Percent
Nervous	22	30.1
Confident	28	38.4
Adaptable	21	28.8
Rigid	2	2.7
Total	73	100.0

b. Finance and Accounting

Hypothesis 2.1

To examine Hypothesis 2.1 (multiple occupation-based personality profiles will be identified), LPA was conducted. The profile solutions 2 to 6 were examined as results provided indications that models with more profiles are not needed to identify the appropriate number of latent profiles. These LPAs resulted in a set of model fit statistics and information criteria. A summary of these results is reported in Table 32.

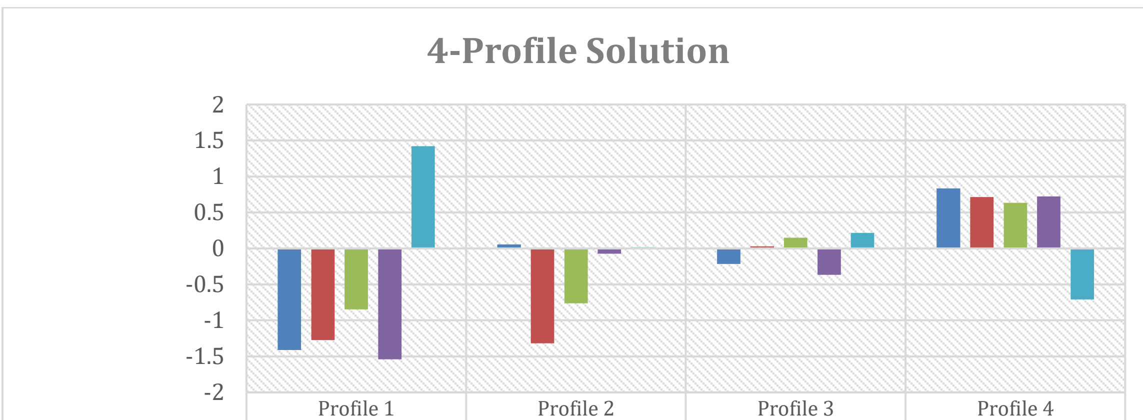
Table 32

Model fit statistics for the 2- to 6-profile models.

No.	AIC	BIC	SABIC	Entropy	VLMR	*p*	LMR	*p*	BLRT	*p*
2	5568.86	5633.69	5582.92	0.69	-2944.70	0.005	343.10	0.006	-2944.70	0
3	5442.98	5532.13	5462.32	0.77	-2768.43	0.000	134.18	0.000	-2768.43	0
4	**5416.53**	**5529.98**	**5441.13**	**0.76**	**-2699.49**	**0.073**	**37.43**	**0.079**	**-2699.49**	**0**
5	5393.59	**5531.36**	5423.46	0.79	-2680.26	0.200	34.00	0.206	-2680.26	0
6	5386.60	5548.69	5421.75	0.71	-2662.79	0.118	18.47	0.124	-2662.79	0.21

The results in Table 32 show that the first guiding factor (BIC) had declining values until profile solution 5, where it started to increase, which supports the selection of the 4-profile solution. The second guiding factor (BLRT) showed significant *p*-values across the examined profile solutions until it became non-significant at the 6-profile solution; hence, this indicated that a 5-

profile solution may be preferable. The third guiding factor (SABIC) showed declining values across all examined profile solutions; therefore, it was deemed not helpful in supporting a specific profile solution. The fourth guiding factor (LMR) showed significant *p*-values until it reached the 4-profile solution where it turned non-significant, indicating that the model with 3-profiles may be preferable. The fifth guiding factor was interpretability, and the 4-profile solution (see Figure 7) was perhaps best in terms of this criterion. Thus, these factors suggest choosing between 3, 4, or 5 profile solutions. Ultimately, a decision was made to select the 4-profile solution based on the BIC and interpretability criteria.



	Profile 1	Profile 2	Profile 3	Profile 4
Openness	-1.411	0.057	-0.214	0.833
Agreeableness	-1.274	-1.32	0.031	0.714
Conscientiousness	-0.845	-0.764	0.148	0.634
Extraversion	-1.539	-0.071	-0.366	0.722
Neuroticism	1.42	0.016	0.217	-0.71

Figure 7. Four latent occupation-based personality profiles solution by mean Big Five scores for Finance and Accounting.

Furthermore, additional pieces of information that were provided in the LPA results for the 4-profile solution indicate the adequacy of this solution. The counts and proportions of the four profiles show each profile represents more than 5% of the dataset, in line with the recommendation from Nylund et al. (2007), as shown in Table 33.

Table 33

Profile Counts and Proportions

Profile	Count	Percentage
1	44	10.4
2	32	7.5
3	221	52.0
4	128	30.1

Also, the classification probabilities for the most likely latent profile membership by latent profile indicates high likelihoods of participants being classified to an appropriate profile, with probabilities ranging from .674 to .899, as shown in Table 34. Based on these results, Hypothesis 2.1 (multiple occupation-based personality profiles will be identified) was supported.

Table 34

Classification probabilities for the most likely latent profile membership (column) by latent profile (row).

	1	2	3	4
1	**0.899**	0.024	0.077	0.000
2	0.027	**0.674**	0.280	0.020
3	0.016	0.022	**0.898**	0.064
4	0.000	0.005	0.138	**0.856**

For ease of reference and interpretability, the profiles were again labeled. Upon visually examining the graph representing the four profiles (Figure 7), it was clear that two of them are very similar to the organization-based profiles identified in Section 1. Therefore, a judgement was made to give them the same labels, where profile 1 is “rigid”, and profile 4 is “adaptable”. Two other distinctive profiles were identified. Profile 2 was characterized by below average agreeableness and conscientiousness. A judgement was made to label this profile as “inconsiderate” as explained later in the discussion section. Finally, profile 3 was characterized by slightly below average openness and extraversion and slightly above average neuroticism and conscientiousness. A judgement was made to label this profile as “ordinary” as also explained later in the discussion section.

Hypothesis 2.2

To examine Hypothesis 2.2 (occupation-based personality profiles will have a contribution above and beyond both personality traits and organization-based personality profiles in predicting job performance), regression analyses were conducted using overall job performance and the individual job performance dimensions as separate dependent variables. Given that the organizational-based profiles in Section 1 were found to have higher validity in the form of continuous variables rather than categorical variables, only the set of continuous variables will be used to represent the contribution of organization-based profiles in these analyses.

First, multiple linear regression analyses were conducted to explore the predictive ability of personality traits, organization-based personality profiles, and occupation-based personality profiles (categorical and continuous) for job performance. Second, hierarchical regression analyses were conducted to examine the contribution of occupation-based personality profiles above and beyond personality traits and organization-based personality profiles.

The initial multiple linear regression analyses show the results for personality traits, organization-based personality profiles, and occupation-based personality profiles (categorical and continuous) in predicting overall job performance (see the summary in Table 35; see further information in Appendix E). The results provided in Table 35 show comparable validity values for personality traits and occupation-based profiles, followed by organization-based profiles as predictors of overall job performance. Within these three sets of profiles, it can be observed that validity was higher for occupation-based profiles, followed by the organization-based profiles.

Table 35

Summary of Regression Analyses for Overall Performance

IV: Traits		IV: Org-Based Profiles		IV: Occ-Based Profiles (Categorical)		IV: Occ-Based Profiles (Continuous)	
R	R^2	*R*	R^2	*R*	R^2	*R*	R^2
$.197^{**}$	.039	$.151^{*}$	.023	$.190^{**}$	.036	$.181^{**}$	.033

$^{*}p < .05$, $^{**}p < .01$.

A one-way ANOVA was further conducted to provide another way to look at and explain the effect of profile membership on job performance levels (Table 36). This analysis showed significant differences in the levels of overall job performance based on profile membership (F (3,421) = 5.245, p = .001), and further information can be seen in Appendix E. Table 37 shows the means of performance across the four profiles. As for mean performance levels, it is shown that performance is ranked in descending order from inconsiderate, adaptable, to ordinary, to rigid.

Table 36

One-way ANOVA Results for Profiles using Overall Performance as the Criterion

Source	Sum of Squares	*df*	Mean Square	*F*	Sig.	Partial Eta Squared
Between Groups	8.955	3	2.985	5.245	.001	.036
Within Groups	239.602	421	.569			
Total	248.557	424				

Table 37

Means of Overall Performance Across Profiles

Profile	Mean	SD
Rigid	-.290	.810
Inconsiderate	.394	.655
Ordinary	.027	.781
Adaptable	.071	.709

The incremental validity of both occupation-based categorical and continuous profiles in predicting overall job performance was then examined using a hierarchical regression analysis where traits are added in the first step, organization-based profiles are added in the second step, and occupation-based profiles are added in the third step. Table 38 shows a summary of the analyses where occupation-based profiles did not provide significant incremental validity over both traits and organization-based profiles. This table also shows results for analyses involving organization-based profiles added in the final step. Results indicated the organization-based profiles did not provide significant incremental validity over both traits and occupation-based profiles.

Table 38

Summary of Hierarchical Regression Analysis for Overall Performance with Significant Results

Model	*R*	R^2	R^2 change
1. Traits	$.197^{**}$	.039	$.039^{**}$
2. Org-Based Profiles	$.230^{**}$	.053	.014
3. Occ-Based Profiles (Categorical)	$.247^{**}$	.061	.008
1. Traits	$.197^{**}$	.039	$.039^{**}$
2. Org-Based Profiles	$.230^{**}$	.053	.014
3. Occ-Based Profiles (Continuous)	$.240^{*}$	.058	.004
1. Traits	$.197^{**}$	.039	$.039^{**}$
2. Occ-Based Profiles (Categorical)	$.238^{**}$	.057	.018
3. Org-Based Profiles	$.247^{**}$	.061	.004
1. Traits	$.197^{**}$	.039	$.039^{**}$
2. Occ-Based Profiles (Continuous)	$.229^{**}$	.052	.014
3. Org-Based Profiles	$.240^{*}$	.058	.005

$^{*}p < .05$, $^{**}p < .01$.

To examine the incremental validity of profiles in predicting individual job performance dimensions, initial multiple linear regression analyses were conducted to show the criterion-related validity of occupation-based profiles (categorical and continuous) in predicting each of the job performance dimensions as shown in Table 39. The two sets of personality profiles were found to be mostly significant in predicting job performance dimensions, with the exception of non-significant prediction of Leverages Mastery and Builds Diverse, Collaborative Relationships ($p >$

.05). Note also that the validity values were more frequently higher for the categorical profiles than the continuous profiles for this occupation in predicting performance dimensions.

Table 39

Summary of Regression Analysis for Individual Performance Dimensions

IV: Occ-Based Profiles (Categorical)		IV: Occ-Based Profiles (Continuous)	
R	R^2	*R*	R^2
DV: Thinks and Acts Decisively			
.196**	.039	.184**	.034
DV: Leverages Mastery			
.107	.011	.122	.015
DV: Innovates and Reapplies			
.193**	.037	.191**	.037
DV: Leads			
.164**	.027	.177**	.031
DV: Builds Diverse, Collaborative Relationships			
.108	.012	.116	.013
DV: Grows Capability			
.185**	.034	.174**	.030
DV: In Touch			
.147*	.022	.124	.015
DV: Embraces Change			
.167**	.028	.164**	.027
DV: Operates with Discipline			
.175**	.031	.154*	.024

*$p < .05$, **$p < .01$.

To test for the incremental validity of occupation-based categorical and continuous profiles in predicting individual performance dimensions, hierarchical regression analyses were conducted where the first step included traits, the second step included organization-based profiles, and the third step included occupation-based profiles for each of the nine job performance dimensions. None of the analyses were found to be significant. Further information on all of the hierarchical regression analyses, including the significant and non-significant results, can be seen in Appendix E.

As an additional analysis, Table 40 shows results where occupation-based profiles provided significant incremental validity above and beyond traits only. This table also shows results for analyses involving organization-based profiles added in the final step. Note that the dimension of Thinks and Acts Decisively involved notable incremental validity for both categorical and continuous profiles above and beyond traits ($p < .05$), where the overall validity of the model changed from ($R = .215$) to ($R = .263$) when categorical occupation-based profiles were added, and ($R = .254$) when continuous occupation-based profiles were added. Similarly, the dimension of Grows Capability involved incremental validity for categorical occupation-based profiles ($p < .05$), where the overall validity of the model changed from ($R = .177$) to ($R = .230$) after the addition of categorical occupation-based profiles to the model.

Table 40

Summary of Hierarchical Regression Analysis for Performance Dimensions with Significant Results

Model	R	R^2	R^2 change
DV: Thinks and Acts Decisively			
1. Traits	$.215^{**}$	.046	$.046^{**}$
2. Org-Based Profiles	$.260^{***}$	.067	$.021^{*}$
3. Occ-Based Profiles (Categorical)	$.276^{**}$	.076	.009
DV: Thinks and Acts Decisively			
1. Traits	$.215^{**}$	.046	$.046^{**}$
2. Org-Based Profiles	$.260^{***}$	.067	$.021^{*}$
3. Occ-Based Profiles (Continuous)	$.267^{**}$	.071	.004
DV: Thinks and Acts Decisively			
1. Traits	$.215^{**}$	.046	$.046^{**}$
2. Occ-Based Profiles (Categorical)	$.263^{***}$	.069	$.023^{*}$
3. Org-Based Profiles	$.276^{**}$	.076	.007
DV: Thinks and Acts Decisively			
1. Traits	$.215^{**}$	.046	$.046^{**}$
2. Occ-Based Profiles (Continuous)	$.254^{***}$	.065	$.018^{*}$
3. Org-Based Profiles	$.267^{**}$	.071	.007
DV: Grows Capability			
1. Traits	$.177^{*}$	.031	$.031^{*}$
2. Org-Based Profiles	$.213^{*}$	.045	.014
3. Occ-Based Profiles (Categorical)	$.246^{**}$	.060	.015
DV: Grows Capability			
1. Traits	$.177^{*}$	.031	$.031^{*}$
2. Org-Based Profiles	$.213^{*}$	.045	.014
3. Occ-Based Profiles (Continuous)	$.237^{*}$	.056	.011

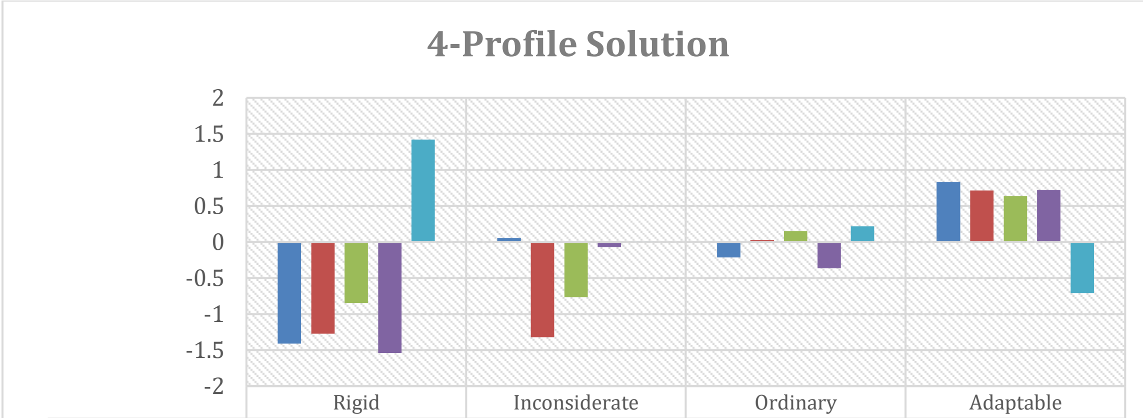
DV: Grows Capability			
1. Traits	.177*	.031	.031*
2. Occ-Based Profiles (Categorical)	.230**	.053	.021*
3. Org-Based Profiles	.246**	.060	.007
DV: Grows Capability			
1. Traits	.177*	.031	.031*
2. Occ-Based Profiles (Continuous)	.218**	.048	.016
3. Org-Based Profiles	.237*	.056	.009

$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

Based on all of the results of the hierarchical regression analyses in predicting overall job performance and the individual job performance dimensions, Hypothesis 2.2 (occupation-based personality profiles will have a contribution above and beyond both personality traits and organization-based personality profiles in predicting job performance) was unsupported.

Research Question

Finally, the Research Question (what is the distribution of personality profiles for the top 10% of performers in the organization and within occupations) was examined. Figure 8 below shows the four personality profiles identified with labels for ease of reference.



	Rigid	Inconsiderate	Ordinary	Adaptable
Openness	-1.411	0.057	-0.214	0.833
Agreeableness	-1.274	-1.32	0.031	0.714
Conscientiousness	-0.845	-0.764	0.148	0.634
Extraversion	-1.539	-0.071	-0.366	0.722
Neuroticism	1.42	0.016	0.217	-0.71

Figure 8. Four latent occupation-based personality profiles solution by mean Big Five scores for Finance and Accounting (Labeled).

Also, Table 41 shows the frequencies of organization-based and occupation-based profiles with the finance and accounting occupation. The frequencies indicate that the ordinary and adaptable profiles were the most common.

Table 41

Frequencies of Profiles Within Finance and Accounting

Occupation-Based Profiles	Frequency	Organization Based Profiles	Frequency
Rigid	44 (10.4%)	Adaptable	61 (14.4%)
Inconsiderate	32 (7.5%)	Rigid	29 (6.8%)
Ordinary	221 (52%)	Confident	200 (47.1%)
Adaptable	128 (30.1%)	Nervous	135 (31.8%)
Total	425	Total	425

An analysis of only the top 10% of performers (n = 41) showed the profile frequencies reported in Table 42. The ordinary profile was found to be the most common in the subset of the top 10% of performers (56.1%) which is higher than their representation in the overall sample (52%), followed by the adaptable profile (26.8%) which is lower than their representation in the overall sample (30.1%), the inconsiderate profile (12.2%) which is higher than their representation in the overall sample (7.5%), and the rigid profile (4.9%) which is lower than their representation in the overall sample (10.4%).

Table 42

Frequencies of Profiles Within the Top 10% of Performers

	Frequency	Percent
Rigid	2	4.9
Inconsiderate	5	12.2
Ordinary	23	56.1
Adaptable	11	26.8
Total	41	100.0

c. Manufacturing Engineering

Hypothesis 2.1

To examine Hypothesis 2.1 (multiple occupation-based personality profiles will be identified), LPA was conducted. The profile solutions 2 to 7 were examined as results provided indications that models with more profiles are not needed to identify the appropriate number of latent profiles. These LPAs resulted in a set of model fit statistics and information criteria. A summary of these results is reported in Table 43.

Table 43

Model fit statistics for the 2- to 7-profile models.

No.	AIC	BIC	SABIC	Entropy	VLMR	*p*	LMR	*p*	BLRT	*p*
2	13639.25	13718.80	13667.98	0.69	-7227.29	0	827.55	0	-7227.29	0
3	13491.90	13601.28	13531.40	0.66	-6803.63	0	155.64	0	-6803.63	0
4	13445.10	13584.30	13495.37	0.68	-6723.95	0.006	57.43	0.007	-6723.95	0
5	**13415.14**	**13584.17**	**13476.18**	**0.68**	**-6694.55**	**0.081**	**40.98**	**0.087**	**-6694.55**	**0**
6	13399.24	**13598.11**	13471.06	0.73	-6673.57	27.24	0.434	0.434	-6673.57	0
7	13387.10	13615.80	13469.70	0.68	-6659.62	0.150	23.58	0.154	-6659.62	0

The results in Table 43 show that the first guiding factor (BIC) had declining values until profile solution 6 where it started to increase again, which supports the selection of the 5-profile solution. The second guiding factor (BLRT) showed significant *p*-values across all examined profile solutions; therefore, it was deemed not helpful in supporting a specific profile solution. The third guiding factor (SABIC) showed declining values across all examined profile solutions, therefore, it was also deemed not helpful in supporting a specific profile solution. The fourth guiding factor (LMR) showed significant *p*-values until it reached the 5-profile solution where it turned non-significant, indicating that the model with 4-profiles may be preferable. The fifth guiding factor was interpretability, and the graph shown in Figure 9 below shows a replicable pattern for all four organization-based profiles identified previously, in addition to one distinctive profile that is similar to the inconsiderate profile identified in the finance and accounting occupation. Therefore, these profiles provide easily interpretable differences between them in line with previous results.

All the previous factors may suggest selection of either 4 or 5 profile solutions; therefore, a judgement was made to choose based on BIC and interpretability, leading to a selection of the 5-profile solution.

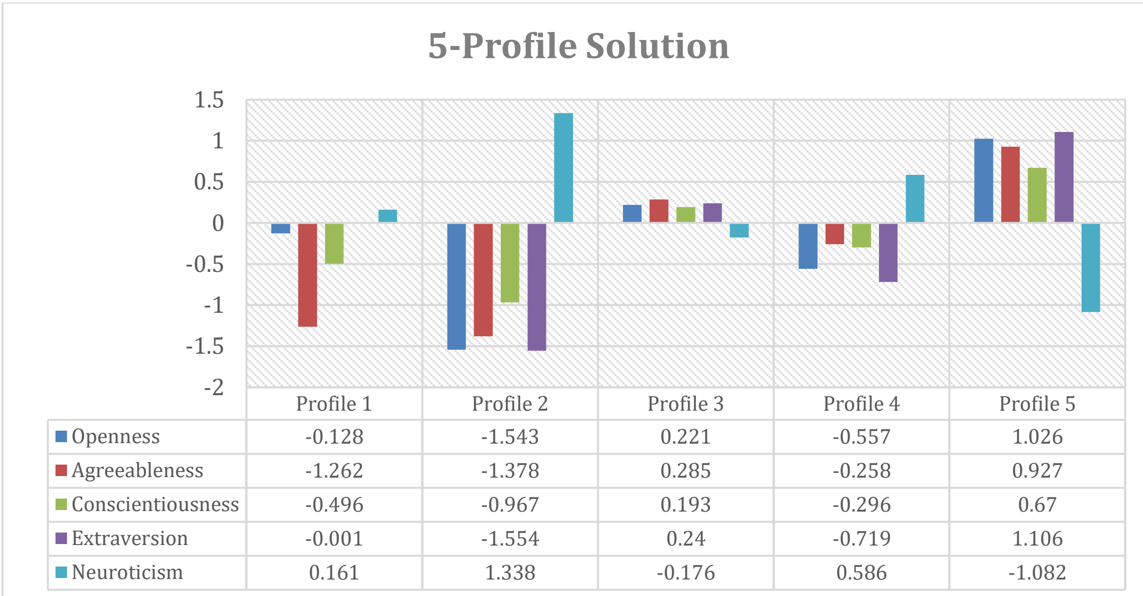


Figure 9. Five latent occupation-based personality profiles solution by mean Big Five scores for Manufacturing Engineering.

Table 44 shows the counts and proportions of the identified five occupation-based profiles and most of them represent individually more than 5% of the dataset.

Table 44

Profile Counts and Proportions

Profile	Count	Percentage
1	40	3.8
2	460	43.2
3	322	30.2
4	63	5.9
5	181	17.0

Also, the classification probabilities for the most likely latent profile membership by latent profile indicates high likelihoods of participants being classified to an appropriate profile, with probabilities ranging from .59 to .819, as shown in Table 45. Based on these results, Hypothesis 2.1 (multiple occupation-based personality profiles will be identified) was supported.

Table 45

Classification probabilities for the most likely latent profile membership (column) by latent profile (row).

	1	2	3	4	5
1	**0.721**	0.000	0.275	0.004	0.000
2	0.000	**0.818**	0.087	0.023	0.072
3	0.024	0.133	**0.819**	0.023	0.000
4	0.005	0.251	0.141	**0.590**	0.013
5	0.000	0.218	0.000	0.005	**0.777**

For ease of reference and interpretability, the profiles were again labeled. Upon visually examining the graph representing the five profiles (Figure 9), it was clear that four of them are very similar to the four organization-based profiles identified in Section 1. Therefore, a judgement was made to give them the same labels, where profile 2 is “rigid”, profile 3 is “confident”, profile 3 is “nervous”, and profile 4 is “adaptable”. One other distinctive profile (profile 1) was identified, which was found to be similar to the inconsiderate profile identified in finance and accounting occupation. Therefore, profile 1 was similarly labeled as “inconsiderate.”

Hypothesis 2.2

To examine Hypothesis 2.2 (occupation-based personality profiles will have a contribution above and beyond both personality traits and organization-based personality profiles in predicting job performance), regression analyses were conducted using overall job performance and the individual job performance dimensions as separate dependent variables. Given that the organizational-based profiles in Section 1 were found to have higher validity values in the form of continuous variables rather than categorical variables, only the set of continuous variables will be used to represent the contribution of organization-based profiles in these analyses.

First, multiple linear regression analyses were conducted to explore the predictive ability of personality traits, organization-based personality profiles, and occupation-based personality profiles (categorical and continuous) for job performance. Second, hierarchical regression analyses were conducted to examine the contribution of occupation-based personality profiles above and beyond personality traits and organization-based personality profiles.

The initial multiple linear regression analyses show the results for personality traits, organization-based personality profiles, and occupation-based personality profiles (categorical and continuous) in predicting overall job performance (see the summary in Table 46; see further information in Appendix F). The results provided in Table 46 show higher validity for traits, followed by the three tested sets of personality profiles as predictors of overall job performance. Within these three sets of profiles, it can be observed that validity was higher for occupation-based profiles in their continuous form.

Table 46

Summary of Regression Analyses for Overall Performance

IV: Traits		IV: Org-Based Profiles		IV: Occ-Based Profiles (Categorical)		IV: Occ-Based Profiles (Continuous)	
R	R^2	R	R^2	R	R^2	R	R^2
$.171^{***}$	.029	$.117^{**}$	.014	$.114^{**}$	.013	$.122^{**}$	.015

$^{**}p < .01$, $^{***}p < .001$.

A one-way ANOVA was further conducted to provide another way to look at and explain the effect of profile membership on job performance levels (Table 47). This analysis showed significant differences in the levels of overall job performance based on profile membership (F (4,1061) = 3.473, $p < .01$), and further information can be seen in Appendix F. Table 48 shows the means of performance across the five profiles. As for mean performance levels, it is shown that performance is ranked in descending order from adaptable, to nervous, to rigid, to confident, to inconsiderate.

Table 47

One-way ANOVA Results for Profiles using Overall Performance as the Criterion

Source	Sum of Squares	*df*	Mean Square	*F*	Sig.	Partial Eta Squared
Between Groups	8.155	4	2.039	3.473	.008	.013
Within Groups	622.810	1061	.587			
Total	630.965	1065				

Table 48

Means of Overall Performance Across Profiles

Profile	Mean	SD
Inconsiderate	-.319	.827
Rigid	.006	.783
Confident	-.093	.726
Nervous	.048	.787
Adaptable	.092	.773

The incremental validity of both occupation-based categorical and continuous profiles in predicting overall job performance was then examined using a hierarchical regression analysis where traits are added in the first step, organization-based profiles are added in the second step, and occupation-based profiles are added in the third step. Table 49 shows a summary of the analyses where occupation-based profiles did not provide significant incremental validity over both traits and organization-based profiles. This table also shows results for analyses involving organization-based profiles added in the final step. Results indicated the organization-based profiles did not provide significant incremental validity over both traits and occupation-based profiles.

Table 49

Summary of Hierarchical Regression Analysis for Overall Performance

Model	*R*	R^2	R^2 change
1. Traits	.171***	.029	.029***
2. Org-Based Profiles	.184***	.034	.005
3. Occ-Based Profiles (Categorical)	.189***	.036	.002
1. Traits	.171***	.029	.029***
2. Org-Based Profiles	.184***	.034	.005
3. Occ-Based Profiles (Continuous)	.200***	.040	.006
1. Traits	.171***	.029	.029***
2. Occ-Based Profiles (Categorical)	.183***	.033	.004
3. Org-Based Profiles	.189***	.036	.002
1. Traits	.171***	.039	.029***
2. Occ-Based Profiles (Continuous)	.191***	.052	.007
3. Org-Based Profiles	.200***	.058	.003

$^{***}p < .001$.

To examine the incremental validity of profiles in predicting individual job performance dimensions, initial multiple linear regression analyses were conducted to show the criterion-related validity of occupation-based profiles (categorical and continuous) in predicting each of the job performance dimensions as shown in Table 50. The two sets of personality profiles were found to be significant in predicting 6 out of 9 job performance dimensions. Note also that the validity values were mostly higher for the continuous profiles than the categorical.

Table 50

Summary of Regression Analysis for Individual Performance Dimensions

IV: Occ-Based Profiles (Categorical)		IV: Occ-Based Profiles (Continuous)	
R	R^2	R	R^2
DV: Thinks and Acts Decisively			
.116**	.013	.127**	.016
DV: Leverages Mastery			
.078	.006	.085	.007
DV: Innovates and Reapplies			
.156**	.024	.171**	.029
DV: Leads			
.116**	.013	.122**	.015
DV: Builds Diverse, Collaborative Relationships			
.106*	.011	.096*	.009
DV: Grows Capability			
.093	.009	.099*	.010
DV: In Touch			
.060	.004	.072	.005
DV: Embraces Change			
.108*	.012	.115**	.013
DV: Operates with Discipline			
.071	.005	.088	.008

$^{*}p < .05$, $^{**}p < .01$.

To test for the incremental validity of occupation-based categorical and continuous profiles in predicting individual performance dimensions, hierarchical regression analyses were conducted where the first step included traits, the second step included organization-based profiles, and the third step included occupation-based profiles for each of the nine job performance dimensions. Only 2 analyses out of these 18 were found to be significant, involving the dimension of Leads as seen in Table 51. This table also shows results for analyses involving organization-based profiles added in the final step. Further information on all of the hierarchical regression analyses, including the significant and non-significant results, can be seen in Appendix F. As observed in Table 51, the dimension of Leads involved incremental validity for both categorical and continuous profiles above and beyond both traits and organization-based profiles.

Table 51

Summary of Hierarchical Regression Analysis for Individual Performance Dimensions with Significant Results

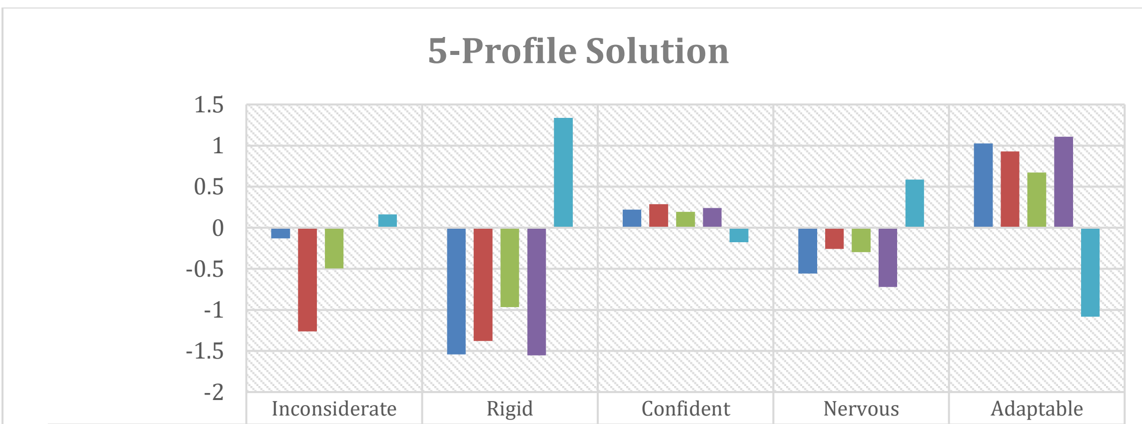
Model	R	R^2	R^2 change
DV: Leads			
1. Traits	$.217^{***}$	.047	$.047^{***}$
2. Org-Based Profiles	$.232^{***}$	.054	.007
3. Occ-Based Profiles (Categorical)	$.254^{***}$	.064	$.010^{*}$
DV: Leads			
1. Traits	$.217^{***}$	.047	$.047^{***}$
2. Org-Based Profiles	$.232^{***}$	.054	.007
3. Occ-Based Profiles (Continuous)	$.269^{***}$	.072	$.018^{***}$
DV: Leads			
1. Traits	$.217^{***}$	.047	$.047^{***}$
2. Occ-Based Profiles (Categorical)	$.243^{***}$	.059	$.012^{**}$
3. Org-Based Profiles	$.254^{***}$	.064	.005
DV: Leads			
1. Traits	$.217^{***}$	.046	$.047^{***}$
2. Occ-Based Profiles (Continuous)	$.248^{***}$	.065	$.014^{**}$
3. Org-Based Profiles	$.269^{***}$	.071	$.011^{**}$

$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

Based on all of the results of the hierarchical regression analyses in predicting overall job performance and the individual job performance dimensions, Hypothesis 2.2 (occupation-based personality profiles will have a contribution above and beyond both personality traits and organization-based personality profiles in predicting job performance) was mostly unsupported.

Research Question

Finally, the Research Question (what is the distribution of personality profiles for the top 10% of performers in the organization and within occupations) was examined. Figure 10 below shows the five personality profiles identified with labels for ease of reference.



	Inconsiderate	Rigid	Confident	Nervous	Adaptable
Openness	-0.128	-1.543	0.221	-0.557	1.026
Agreeableness	-1.262	-1.378	0.285	-0.258	0.927
Conscientiousness	-0.496	-0.967	0.193	-0.296	0.67
Extraversion	-0.001	-1.554	0.24	-0.719	1.106
Neuroticism	0.161	1.338	-0.176	0.586	-1.082

Figure 10. Five latent occupation-based personality profiles solution by mean Big Five scores for Manufacturing Engineering (Labeled).

Also, Table 52 shows the frequencies of organization-based and occupation-based profiles with the manufacturing engineering occupation. The frequencies indicate that the rigid profile was the most common in the occupation (43.2%), followed by the confident profile (30.2%), while the inconsiderate profile was the least common in the data (3.8%).

Table 52

Frequencies of Profiles Within Manufacturing Engineering

Occupation-Based Profiles	Frequency	Organization Based Profiles	Frequency
Inconsiderate	40 (3.8%)	Adaptable	140 (13.1%)
Rigid	460 (43.2%)	Rigid	44 (4.1%)
Confident	322 (30.2%)	Confident	503 (47.2%)
Nervous	63 (5.9%)	Nervous	379 (35.6%)
Adaptable	181 (17%)		
Total	1066	Total	1066

An analysis of only the top 10% of performers (*n* = 106) showed the profile frequencies reported in Table 53. The rigid profile was found to be the most common in the subset of the top 10% of performers (47.2%) which is higher than their representation in the overall sample (43.2%), followed by the adaptable profile (21.7%) which is higher than their representation in the overall sample (17%), the confident profile (20.8%) which is lower than their representation in the overall sample (30.2%), the nervous profile (10.4%) which is higher than their representation in the overall sample (5.9%), and the inconsiderate profile was not represented in this segment.

Table 53

Frequencies of Profiles Within the Top 10% of Performers

	Frequency	Percent
Inconsiderate	0	0
Rigid	50	47.2
Confident	22	20.8
Nervous	11	10.4
Adaptable	23	21.7
Total	106	100.0

d. Research and Development

Hypothesis 2.1

To examine Hypothesis 2.1 (multiple occupation-based personality profiles will be identified), LPA was conducted. The profile solutions 2 to 7 were examined as results provided indications that models with more profiles are not needed to identify the appropriate number of latent profiles. These LPAs resulted in a set of model fit statistics and information criteria. A summary of these results is reported in Table 54.

Table 54

Model fit statistics for the 2- to 7-profile models.

No.	AIC	BIC	SABIC	Entropy	VLMR	*p*	LMR	*p*	BLRT	*p*
2	11387.60	11463.86	11413.05	0.73	-6073.41	0	772.20	0	-6073.41	0
3	11171.02	11275.87	11206.01	0.73	-5677.80	0	223.09	0	-5677.80	0
4	11131.74	11265.19	11176.27	0.67	-5563.51	0.01	50.05	0.02	-5563.51	0
5	**11102.08**	**11264.13**	**11156.16**	**0.71**	**-5537.87**	**0.33**	**40.65**	**0.34**	**-5537.87**	**0**
6	11090.47	**11281.11**	11154.08	0.68	-5517.04	0.24	23.05	0.25	-5517.04	0
7	11076.02	11295.26	11149.18	0.68	-5505.23	0.18	25.81	0.19	-5505.23	0.01

The results in Table 54 show that the first guiding factor (BIC) had declining values until profile solution 6 where it started to increase, which supports the selection of the 5-profile solution.

The second guiding factor (BLRT) showed significant *p*-values across all examined profile solutions; therefore, it was deemed not helpful in supporting a specific profile solution. The third guiding factor (SABIC) showed declining values across all examined profile solutions, therefore, it was also deemed not helpful in supporting a specific profile solution. The fourth guiding factor (LMR) showed significant *p*-values until it reached the 5-profile solution where it turned non-significant, indicating that the model with 4-profiles may be preferable. The fifth guiding factor was interpretability, and the graph shown in Figure 11 below shows a replicable pattern for all four organization-based profiles identified previously, in addition to one distinctive profile that overlaps with the inconsiderate profile identified in the finance and accounting occupation, but is different in having a high level of openness which is very relevant to the research and development capacity. Therefore, these profiles can provide easily interpretable differences between them in line with previous results.

All the previous factors may suggest a selection of either 4 or 5 profile solutions; therefore, a judgement was made to choose based on the BIC and interpretability, leading to a selection of the 5-profile solution.

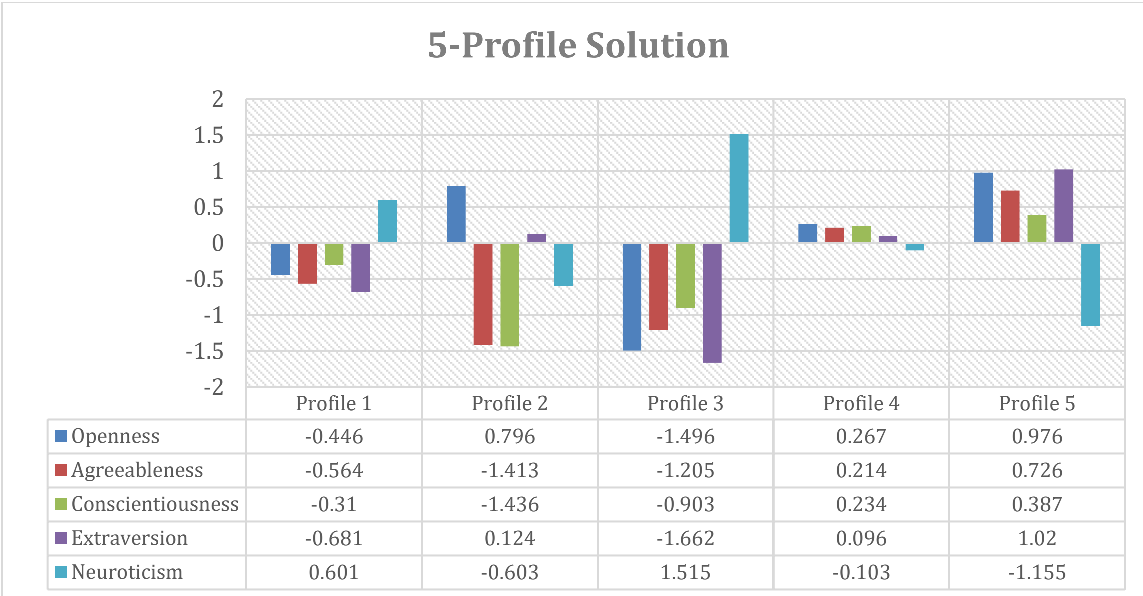


Figure 11. Five latent occupation-based personality profiles solution by mean Big Five scores for Research and Development.

Table 55 shows the counts and proportions of the identified five occupation-based profiles and most of them represent individually more than 5% of the dataset.

Table 55

Profile Counts and Proportions

Profile	Count	Percentage
1	265	30.5
2	13	1.5
3	76	8.8
4	377	43.4
5	137	15.8

Also, the classification probabilities for the most likely latent profile membership by latent profile indicates high likelihoods of participants being classified to an appropriate profile, with probabilities ranging from .62 to .837, as shown in Table 56. Based on these results, Hypothesis 2.1 (multiple occupation-based personality profiles will be identified) was supported.

Table 56

Classification probabilities for the most likely latent profile membership (column) by latent profile (row).

	1	2	3	4	5
1	**0.793**	0.003	0.042	0.162	0.000
2	0.152	**0.626**	0.000	0.191	0.030
3	0.184	0.000	**0.816**	0.000	0.000
4	0.109	0.002	0.000	**0.837**	0.052
5	0.000	0.001	0.000	0.216	**0.783**

For ease of reference and interpretability, the profiles were again labeled. Upon visually examining the graph representing the five profiles (Figure 11), it was clear that four of them are very similar to the four organization-based profiles identified in Section 1. Therefore, a judgement was made to give them the same labels, where profile 1 is “nervous”, profile 3 is “rigid”, profile 4 is “confident”, and profile 5 is “adaptable”. One other distinctive profile (profile 2) was identified, which was found to be similar to the inconsiderate profile identified in the finance and accounting occupation, but different in having above average openness. It was decided to label it “curious,” as later explained in the discussion section.

Hypothesis 2.2

To examine Hypothesis 2.2 (occupation-based personality profiles will have a contribution above and beyond both personality traits and organization-based personality profiles in predicting job performance), regression analyses were conducted using overall job performance and the individual job performance dimensions and as separate dependent variables. Given that the organizational-based profiles in Section 1 were found to have higher validity values in the form of continuous variables rather than categorical variables, only the set of continuous variables will be used to represent the contribution of organization-based profiles in these analyses.

First, multiple linear regression analyses were conducted to explore the predictive ability of personality traits, organization-based personality profiles, and occupation-based personality profiles (categorical and continuous) for job performance. Second, hierarchical regression analyses were conducted to examine the contribution of occupation-based personality profiles above and beyond personality traits and organization-based personality profiles.

The initial multiple linear regression analyses show the results for personality traits, organization-based personality profiles, and occupation-based personality profiles (categorical and continuous) in predicting overall job performance (see the summary in Table 57; see further information in Appendix G). The results provided in Table 57 show higher validity value for traits, followed by organization-based profiles and occupation-based profiles in their continuous form, and then occupation-based profiles in their categorical form as predictors of overall job performance. Within the three sets of profiles, it can be observed that validity was slightly higher for organization-based profiles and continuous occupation-based profiles, followed by the occupation-based profiles in their categorical form.

Table 57

Summary of Regression Analyses for Overall Performance

IV: Traits		IV: Org-Based Profiles		IV: Occ-Based Profiles (Categorical)		IV: Occ-Based Profiles (Continuous)	
R	R^2	*R*	R^2	*R*	R^2	*R*	R^2
$.221^{***}$	.049	$.201^{***}$	.040	$.174^{***}$	.030	$.198^{***}$	.039

$^{***}p < .001$.

A one-way ANOVA was further conducted to provide another way to look at and explain the effect of profile membership on job performance levels (Table 58). This analysis showed significant differences in the levels of overall job performance based on profile membership (F (4,863) = 6.709, $p < .001$), and further information can be seen in Appendix G. Table 59 shows the means of performance across the five profiles. As for mean performance levels, it is shown that performance is ranked in descending order from adaptable, to confident, to curious, to nervous, to rigid.

Table 58

One-way ANOVA Results for Profiles using Overall Performance as the Criterion

Source	Sum of Squares	*df*	Mean Square	*F*	Sig.	Partial Eta Squared
Between Groups	15.526	4	3.882	6.709	.000	.030
Within Groups	499.293	863	.579			
Total	514.819	867				

Table 59

Means of Overall Performance Across Profiles

Profile	Mean	SD
Nervous	-.023	.738
Curious	.111	.634
Rigid	-.303	.685
Confident	.121	.765
Adaptable	.190	.838

The incremental validity of both occupation-based categorical and continuous profiles in predicting overall job performance was then examined using a hierarchical regression analysis where traits are added in the first step, organization-based profiles are added in the second step, and occupation-based profiles are added in the third step. Table 60 shows a summary of the analyses where occupation-based profiles did not provide significant incremental validity over both traits and organization-based profiles. This table also shows results for analyses involving organization-based profiles added in the final step. Results indicated the organization-based profiles did not provide significant incremental validity over both traits and occupation-based profiles.

Table 60

Summary of Hierarchical Regression Analysis for Overall Performance

Model	R	R^2	R^2 change
1. Traits	.221***	.049	.049***
2. Org-Based Profiles	.236***	.056	.007
3. Occ-Based Profiles (Categorical)	.249***	.062	.006
1. Traits	.221***	.049	.049***
2. Org-Based Profiles	.236***	.056	.007
3. Occ-Based Profiles (Continuous)	.238***	.057	.001
1. Traits	.221***	.049	.049***
2. Occ-Based Profiles (Categorical)	.233***	.055	.006
3. Org-Based Profiles	.249***	.062	.007
1. Traits	.221***	.049	.049***
2. Occ-Based Profiles (Continuous)	.236***	.056	.007
3. Org-Based Profiles	.238***	.057	.001

***$p < .001$.

To examine the incremental validity of profiles in predicting individual job performance dimensions, initial multiple linear regression analyses were conducted to show the criterion-related validity of occupation-based profiles (categorical and continuous) in predicting each of the job performance dimensions as shown in Table 61. The two sets of personality profiles were found to be significant in predicting 8 out of 9 job performance dimensions. Note also that the validity values were mostly higher for the continuous profiles than the categorical.

Table 61

Summary of Regression Analysis for Individual Performance Dimensions

IV: Occ-Based Profiles (Categorical)		IV: Occ-Based Profiles (Continuous)	
R	R^2	*R*	R^2
DV: Thinks and Acts Decisively			
$.167^{***}$	.028	$.198^{***}$	.039
DV: Leverages Mastery			
$.151^{**}$	.023	$.173^{***}$	.030
DV: Innovates and Reapplies			
$.182^{***}$	.033	$.206^{***}$	.043
DV: Leads			
$.175^{***}$	.031	$.187^{***}$	.035
DV: Builds Diverse, Collaborative Relationships			
$.164^{***}$	.027	$.186^{***}$	.035
DV: Grows Capability			
$.131^{**}$	.017	$.148^{**}$	.022
DV: In Touch			
.079	.006	.099	.010
DV: Embraces Change			
$.159^{***}$	.025	$.181^{***}$	.033
DV: Operates with Discipline			
$.115^{*}$	.013	$.127^{**}$	.016

$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

To test for the incremental validity of occupation-based categorical and continuous profiles in predicting individual performance dimensions, hierarchical regression analyses were conducted where the first step included traits, the second step included organization-based profiles, and the third step included occupation-based profiles for each of the nine job performance dimensions. None of the analyses was found to be significant. Further information on all of the hierarchical regression analyses, including the significant and non-significant results, can be seen in Appendix G.

As an additional analysis, Table 62 shows the results where occupation-based profiles provided significant incremental validity above and beyond traits only. This table also shows results for analyses involving organization-based profiles added in the final step. Note that the dimension of Leads involved incremental validity for continuous occupation-based profiles ($p < .05$), where the overall validity of the model changed from ($R = .219$) to ($R = .243$) after the addition of continuous occupation-based profiles to the model.

Table 62

Summary of Hierarchical Regression Analysis for Individual Performance Dimensions with Significant Results

Model	R	R^2	R^2 change
DV: Leads			
1. Traits	$.219^{***}$	.048	$.048^{***}$
2. Org-Based Profiles	$.236^{***}$	.056	.008
3. Occ-Based Profiles (Categorical)	$.250^{***}$	.063	.007
DV: Leads			
1. Traits	$.219^{***}$	.048	$.048^{***}$
2. Org-Based Profiles	$.236^{***}$	.056	.008
3. Occ-Based Profiles (Continuous)	$.245^{***}$	.060	.004
DV: Leads			
1. Traits	$.219^{***}$	.048	$.048^{***}$
2. Occ-Based Profiles (Categorical)	$.239^{***}$	.057	.009
3. Org-Based Profiles	$.250^{***}$	.063	.005

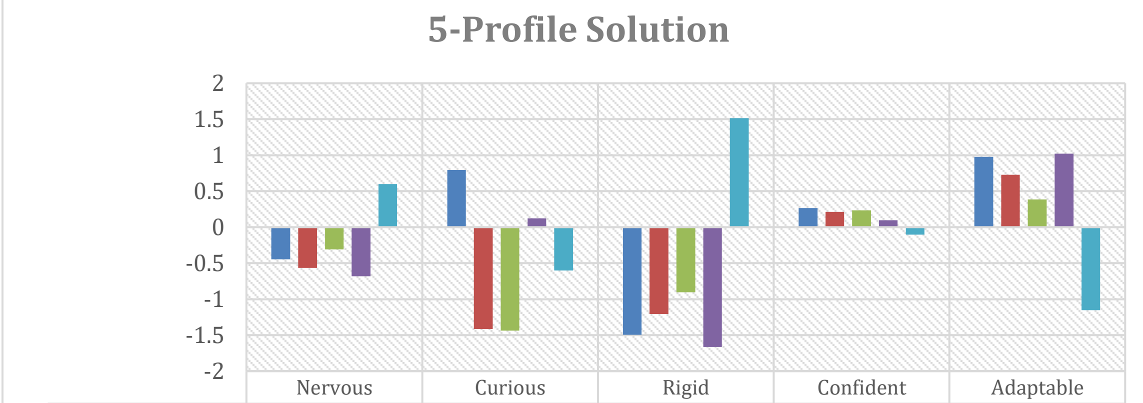
DV: Leads			
1. Traits	.219***	.048	.048***
2. Occ-Based Profiles (Continuous)	.243***	.059	.011*
3. Org-Based Profiles	.246***	.060	.001

*$p < .05$, ***$p < .001$.

Based on all of the results of the hierarchical regression analyses in predicting overall job performance and the individual job performance dimensions, Hypothesis 2.2 (occupation-based personality profiles will have a contribution above and beyond both personality traits and organization-based personality profiles in predicting job performance) was unsupported.

Research Question

Finally, the Research Question (what is the distribution of personality profiles for the top 10% of performers in the organization and within occupations) was examined. Figure 12 below shows the five personality profiles identified with labels for ease of reference.



	Nervous	Curious	Rigid	Confident	Adaptable
Openness	-0.446	0.796	-1.496	0.267	0.976
Agreeableness	-0.564	-1.413	-1.205	0.214	0.726
Conscientiousness	-0.31	-1.436	-0.903	0.234	0.387
Extraversion	-0.681	0.124	-1.662	0.096	1.02
Neuroticism	0.601	-0.603	1.515	-0.103	-1.155

Figure 12. Five latent occupation-based personality profiles solution by mean Big Five scores for Research Development (Labeled).

Also, Table 63 shows the frequencies of organization-based and occupation-based profiles within the research and development occupation. The frequencies indicate that the confident profile was the most common in the occupation (43.4%), followed by the nervous profile (30.5%), the adaptable profile (15.8%), the rigid profile (8.08%), and then the curious profile (1.5%).

Table 63

Frequencies of Profiles Within Research and Development

Occupation-Based Profiles	Frequency	Organization Based Profiles	Frequency
Nervous	265 (30.5%)	Adaptable	120 (13.8%)
Curious	13 (1.5%)	Rigid	69 (7.9%)
Rigid	76 (8.08%)	Confident	397 (45.7%)
Confident	377 (43.4%)	Nervous	282 (32.5%)
Adaptable	137 (15.8%)		
Total	868	Total	868

An analysis of only the top 10% of performers (*n* = 89) showed the profile frequencies reported in Table 64. The confident profile was found to be the most common in the subset of the top 10% of performers (48.3%) which is higher than their representation in the overall sample (43.4%), followed by the nervous profile (25.8%) which is lower than their representation in the overall sample (30.5%), the adaptable profile (24.7%) which is higher than their representation in the overall sample (15.8%), the rigid profile (1.1%) which is lower than their representation in the overall sample (8.08%), and the curious profile was not represented in this top 10% segment. It is interesting that although the curious profile had the third rank in terms of average performance rating (Table 59), it was not represented among the top 10% of performers.

Table 64

Frequencies of Profiles Within the Top 10% of Performers

	Frequency	Percent
Nervous	23	25.8
Curious	0	0
Rigid	1	1.1
Confident	43	48.3
Adaptable	22	24.7
Total	89	100.0

Discussion

The current study explores the relationship between personality and job performance in an organizational sample to examine three issues that have received limited attention in the literature. First, this research used a person-centered approach to identify personality profiles in the workplace. Second, the study examined the relationship between personality profiles and job performance, and whether profiles may provide incremental validity over personality traits. Third, this study also investigated the potential relevance of occupations (a) as a moderator in the relationship between personality profiles and job performance and (b) as subsamples to extract occupation-based personality profiles and examine the nature and implications of these occupation-based personality profiles in terms of predicting job performance over organization-based personality profiles and personality traits. As Kulas (2013) showed in his study that in practice 62% of surveyed selection-oriented consultative vendor organizations implement some form of profile matching, this study is an initial attempt to investigate the effectiveness of using similar personality profiles in predicting job performance.

Findings

In summary, in the first section of results, where the full organizational dataset was used for analysis, three main hypotheses were tested. Hypothesis 1.1 (multiple organization-based personality profiles will be identified) was supported. Hypothesis 1.2 (organization-based personality profiles will have a contribution above and beyond personality traits in predicting organization-wide job performance) was partially supported. And Hypothesis 1.3 (occupations will moderate the relationship between organization-based personality profiles and job performance) was mostly unsupported.

In the second section of results, where occupational datasets were used for analysis, two main hypotheses were tested. Hypothesis 2.1 (multiple occupation-based personality profiles will be identified) was supported. And Hypothesis 2.2 (occupation-based personality profiles will have a contribution above and beyond both personality traits and organization-based personality profiles in predicting job performance) was mostly unsupported.

Finally, a Research Question (what the distribution of personality profiles for the top 10% of performers in the organization and within occupations is) was examined. It was common to find the adaptable or the confident profiles highly represented in this top performer segment, while the rigid profile was generally the least represented in this segment.

Although, to the best of our knowledge, no published studies have yet examined personality profiles in a corporate sample, the initial attempt to identify workplace personality profiles through the current study replicated some of the personality profile patterns identified in other contexts. Four organization-based profiles were identified in the current study: adaptable, rigid, confident, and nervous. The adaptable profile can be matched with the resilient profile (Asendorpf et al., 2001; Herzberg & Roth, 2006; Kinnunen et al., 2012; Zhang et al. 2015) and the well-adjusted profile (Ferguson & Hull, 2018; Merz & Roesch, 2011). The rigid profile can be matched with the same labeled profile by Zhang et al. (2015) and the non-desirable profile identified by Rammstedt et al. (2004). The confident profile can also be matched with the same labeled profile by Zhang et al. (2015). Finally, the nervous profile can be matched with the ordinary profile identified by Zhang et al. (2015). The only study that had four matching patterns in the literature for the four identified profiles in this study was Zhang et al. (2015). One possible reason for this is that this study used an adult sample and the sample size was large *(n* = 3110), and therefore it shared some characteristics with the current study. Future studies with large sample sizes and adult or organizational samples may be useful in further examining this possibility.

In labeling profiles, an attempt was made to match the identified profiles in this study with other previously observed profiles that have similar patterns. The goal was to have previous studies inform the current labeling. One of the most common set of labels revealed in the literature search was the combination of "resilient, overcontrolled, and undercontrolled" (Asendorpf, 2015). Despite the prevalence of using these labels even in cases with only partial matching with the characteristics of these three replicated profiles, a discussion by Daljeet et al. (2017) helped inform my decision to not use these labels. Daljeet et al. (2017) argued that these three labels have an origin that dates back to the theory of ego-control and ego-resiliency (Block & Block, 1980), and they were helpful in classifying individuals in terms of their relationship with impulses and self-regulatory processes. However, this use does not necessarily help or inform our understanding when using these labels to identify workplace-related personality profiles and work-related behaviors in relation to organizational environments. Labels should help us describe the characteristics of identified profiles in relation to the context being studied. Therefore, a judgement was made to label the profiles identified in this study in a manner relevant to work and organizational research that would make it easier for us to distinguish different profiles of employees in the corporate world.

A major theme in organizational literature is change management in relation to the dynamic nature of workplaces in response to the competitiveness of global markets. This affects not only the structure of organizations (e.g., mergers and acquisitions), but also the nature of work itself (e.g., new technologies, roles, and tasks). That is why it is important for organizations to search for employees who are able to cope with change and adapt to the changing requirements of the business. Previous studies focused on studying and assessing adaptability at the workplace (e.g., Pulakos, Arad, Donovan, & Plamondon, 2000) and other studies emphasize the importance of employees' adaptability and link it to important organizational outcomes such as job performance (e.g., Cullen, Edwards, Casper, & Gue, 2014). Accordingly, it was decided to characterize the identified profiles in terms of how they may interact with change in the workplace.

The first identified profile was characterized by substantially below average neuroticism and substantially above average openness, agreeableness, conscientiousness, and extraversion. These characteristics might provide employees with ideal personality attributes in relation to responding to change; hence, this profile was labeled adaptable. In support of this notion, evidence of associations between this pattern of personality traits and adaptability has been found previously; for instance, this has been supported in comparing the personalities of aeronautically adaptable military aviators to non-adaptable military aviators (Campbell, Ruiz, & Moore, 2010) and in predicting career adaptability (Avram, Burtaverde, & Zanfirescu, 2019). The second identified profile was essentially the opposite as it was characterized by substantially above average neuroticism and substantially below average openness, agreeableness, conscientiousness, and extraversion. These dispositions might provide employees with the most undesirable personality attributes in relation to responding to change; hence, this profile was labeled rigid, which matched with the label given by Zhang et al. (2015). The third identified profile was characterized by below average neuroticism and above average openness, agreeableness, conscientiousness, and extraversion. These characteristics may be modestly favorable (compared to the ideal profile of adaptable) and may provide employees with useful levels of confidence in dealing with change; hence, this profile was labeled confident. Note that the adaptable profile may also be quite confident; however, the adaptable profile has even more desirable levels of the Big Five and thus may have further adaptive qualities that exceed mere confidence. The fourth profile was almost the opposite of the confident profile as it was characterized by above average neuroticism and below average openness, agreeableness, conscientiousness, and extraversion. These dispositions may put employees in an unfavorable position in dealing with change; hence, this profile was labeled nervous.

Although the occupation-based profiles largely replicated the four identified organization-based profiles, three additional profiles emerged and were also labeled. First, profile 2 in the finance and accounting occupation and profile 1 in manufacturing engineering were characterized by substantially below average agreeableness and conscientiousness. Although this is similar to the undercontrolled profile in the literature (Donnellan & Robins, 2010), an attempt was again made to identify a more organizationally-relevant label. Specifically, these characteristics suggest difficulty in dealing with others and lack of interest in attending to others' situations or work requirements; hence, this profile was labeled inconsiderate. Second, profile 3 in the finance and accounting occupation was characterized by slightly below average extraversion and openness, and slightly above average neuroticism and conscientiousness, which partially matches the overcontrolled profile in the literature (Donnellan & Robins, 2010). In organizational contexts, it may be that relatively low extraversion and openness accompanied by slightly above average neuroticism may refer to an ordinary employee in relation to how they deal with change; hence, this profile was labeled ordinary. Finally, profile 2 in the occupation of research and development was characterized by substantially below average agreeableness, conscientiousness, and neuroticism, and substantially above average openness. These characteristics were similar to the inconsiderate profile but with greater openness, indicating an interest in knowing about or trying what is new; hence, it was labeled curious. The current study made an attempt at exploring occupation-based profiles for four occupations (i.e., sales, finance and accounting, manufacturing engineering, and research and development), and future studies may explore the generalizability of these occupation-specific profiles.

In addition, some readers could suggest that the four identified organization-based profiles provide a consistent pattern where differences between profiles are mainly due to different levels (magnitudes) of average scores of the Big Five dimensions, such that the profiles range from desirable (i.e., adaptable) to relatively-desirable (i.e., confident) to relatively-undesirable (i.e., nervous) to undesirable (i.e., rigid). This notion may suggest that these profiles could simply represent different levels of the Big Five continuous profiles rather than true or meaningful population subgroups. However, some LPA results in this study suggest this may not tell the full story. For example, during the analysis of occupation-based profiles, a few distinctive profiles emerged (inconsiderate, ordinary, and curious). This provides support for the distinctiveness of occupation-based profiles over the prevalent organization-based profiles in the sample being studied and shows that the LPA did not merely provide clusters that represent different levels/magnitudes of the Big Five continuum.

In terms of the effectiveness of personality profiles in predicting performance, organization-based profiles showed slightly lower criterion-related validities compared with personality traits. In addition, these profiles showed minimal incremental validity over personality traits in predicting overall job performance. In predicting individual job performance dimensions, the personality traits tended to have higher criterion-related validity than the organization-based profiles. However, some analyses showed marginal incremental validity of organization-based profiles over personality traits. The incremental validity results for occupation-based profiles were somewhat mixed. Although they did not show incremental validity over personality traits for overall performance, the occupation-based profiles showed some incremental validity over traits, and in some cases over both traits and organization-based profiles, in predicting some of the individual job performance dimensions. This may suggest a potential use for profiles in addition to traits, especially for occupation-based profiles in relation to certain job performance dimensions. A possible reason for these results is that occupation-based profiles, which are more specific to the occupation being studied, can be linked to specific aspects of performance related to the occupation, which is more in line with the concepts of situation specificity and personality-oriented job analysis.

Also, the rationale behind labeling the four organization-based profiles implies an expectation that the profiles may rank as follows in terms of job performance: adaptable, then confident, then nervous, and lastly rigid. This follows the order of how desirable these configurations of personality traits may be in terms of ability to adapt to work-related changes. In examining the relationship between profiles and performance levels, evidence was found that supports this assumption. That is, the adaptable profile had the highest mean performance score, followed by confident, nervous, and rigid. This is also in line with evidence in the literature that has linked the resilient profile (i.e., adaptable) to high levels of job performance in a military sample (Conte et al., 2017).

In examining the distribution of profiles for the top 10% of performers, the assumption of desired order in terms of profiles (adaptable, then confident, then nervous, then rigid) was also supported. The adaptable profile was found to be represented in the group of top performers at a percentage higher than its original representation in the overall sample. Also, the rigid profile was found to be the least represented profile among top performers. However, an interesting observation was that the confident profile was the most represented profile among top performers. This indicates that despite being characterized by less desired trait levels in comparison with the adaptable profile, the confident profile is more prevalent in this context and is also able to deliver higher levels of performance. It can also be observed that occupation-based personality profiles that are most common in an occupation's top 10% of performers may show profiles that are more relevant or important to the specific occupation. For instance, the rigid profile was the most represented in this top 10% segment for the manufacturing engineering occupation. This indicates that a strong inclination to conform with established practices and a limited disposition for changing the status quo—which may be beneficial to this occupation in terms of complying with established practices that prioritize safety for factory-involved staff—was in fact common in the top performer group.

Limitations

The archival nature of the data used in the current study meant there were some methodological limitations. One major example of this is that all of the personality items were not necessarily intended to be mapped on to the Big Five model of personality. Accordingly, the attempt to match the organizational personality items with the Big Five led to fewer items being used than might be ideal as reflected in the relatively low reliability of two of the personality factors: extraversion (.55) and neuroticism (.60). In addition, the item to factor matching may not have been ideal in all cases.

Another limitation is that the data were collected during a concurrent validation project, which involves asking incumbents to respond to the personality items used in the study. This in turn may have resulted in range restriction (i.e., the range of scores may have been restricted relative to a sample involving a wider variety of individuals), which may have attenuated the observed relations between the variables in the current study.

In addition, the job performance measures included in the current dataset were subjective in nature (supervisor ratings) rather than objective. Subjective performance measures can be vulnerable to individual biases, rater errors, and memory recall issues (e.g., Bernardin & Pence, 1980; Nathan & Tippins, 1990; Roch, Woehr, Mishra, & Kieszczynska, 2012). Nonetheless, multiple items were used to assess each performance dimension, and adequate reliability was found for these performance scales (reliability values ranged between .69 and .83).

Another limitation is that supervisor IDs were not available in the dataset. Thus, the extent to which employees were nested within supervisors is not known and any nesting could not be taken into account in the analyses.

Also, a lack of consensus in the literature regarding the optimal way to conduct LPA may have limited our ability to select the most accurate personality profile solution. However, this study did involve a diligent review and application of existing recommendations to increase the likelihood of identifying meaningful profiles.

Finally, it could be argued that the large sample in this study creates the potential for observing fairly trivial effects that are nonetheless statistically significant. Funder and Ozer (2019) discussed the importance of using large samples in research and argued that small effect sizes found in large samples are likely to reflect the reality of the phenomenon being observed in the real world and these can be more accurate than large effect sizes observed in small samples. Therefore, it is important that researchers carry out more studies based on large samples in order to increase the likelihood that the effect sizes are replicable.

Implications and Future Directions

Theoretical implications

One of the main outcomes of this study was the identification of organization-based personality profiles based on a large organizational sample. This can inform researchers regarding the nature and distribution of personality profiles in the workplace. This is especially important as it fills a gap in the literature in that previous published studies have not covered personality profiles in corporate settings and very few have studied the relationship between personality profiles and job performance. Therefore, the identified profiles in the current study can provide important evidence for making comparisons with organization-based personality profiles to be identified in the future. In addition, the argument for labeling personality profiles in a manner relevant to the context and the purpose of this line of research can guide future research efforts in matching patterns of identified profiles with previous findings while also potentially re-labeling profiles in a way that closely addresses the goal of the research.

Additionally, this study assessed the effectiveness of operationalizing personality profiles in terms of categorical variables (i.e., dummy-coded variables) and continuous variables (i.e., probabilities of belonging to each profile) by using both approaches in conducting the analyses. It was found that in most of the cases where personality profiles were significant predictors, the continuous operationalization of profiles provided higher criterion-related validity and incremental validity than the categorical operationalization of profiles. This in turn suggests that future researchers and practitioners should considering using continuous profile variables to obtain more valid results in applying LPA approaches.

In addition, the fact that organization-based personality profiles provided small incremental validity above personality traits despite having lower criterion-related validity suggests that profiles may be capturing additional information in terms of an individual's personality that does not entirely overlap with the information contained in the individual trait levels. Future research might examine this further to determine the extent to which these results hold in other samples and the potential practical value of this small level of incremental validity.

Furthermore, another important contribution of the current study is the introduction and exploration of occupation-based profiles. First, this provided further evidence on the characteristics of the four occupations studied in this research, including the distinctiveness of some identified personality profiles compared to the organization-based profiles. Second, the study showed that occupation-based profiles can in some cases enhance prediction of job performance dimensions when added to personality traits. This finding suggests that these profiles may capture additional information related to personality.

Practical implications

The current study begins to address the call Kulas (2013) made to examine further the effectiveness of personality profiles, as they were found to be frequently used in practice regardless of the limited research on their validity. The current study showed the existence of some significant links between personality profiles and job performance. This is encouraging in terms of further trying to explore the effectiveness of using profiles and understand the optimal conditions for the use of profiles. Profiles in general showed somewhat lower criterion-related validities when compared with personality traits. But in some cases, such as occupation-based profiles that were operationalized as continuous variables and used to predict some performance dimensions, they added incremental validity in predicting job performance dimensions when combined with personality traits. This should encourage practitioners to dig deeper using job analysis techniques to identify significant links between occupation- or organization-specific personality profiles and relevant aspects of job performance. Upon testing and identifying which profiles provide notable incremental validity for performance dimensions, these profiles can be used in combination with traits to provide better prediction for these dimensions.

Furthermore, the results of this study suggest that organizations should search for and maintain candidates with the adaptable profile, while keeping an eye on those with a rigid profile. In addition, the analyses in the current study showed that the top 10% of performers are often those with the confident profile. Therefore, specific attention and development opportunities should be directed to these individuals, because the confident category might be responsible for a large share of the organization's performance.

Future Directions

Future studies might attend to various considerations. First, research should replicate the current study using a dedicated Big Five assessment tool to see if similar results are obtained. Second, future studies should try to replicate the current study across other organizations, industries, and occupations to examine the replicability and generalizability of the current results. Third, research projects need to study different conditions or environments (e.g., organizational cultures or work roles) that may influence the effectiveness of the identified profiles in the workplace. Fourth, future studies need to explore the links between the identified personality profiles and important organizational outcomes other than job performance (e.g., turnover). Fifth, research might examine the relationship between personality profiles and job performance while taking vocational interests into consideration. Finally, additional research designed to identify best practices in LPA particularly related to selecting a model with the right number of profiles could be quite helpful.

Conclusion

The current study focused on identifying personality profiles in the workplace by analyzing archival data from a large international organization. This resulted in the identification of four organization-based profiles (adaptable, rigid, confident, and nervous) and occupation-based profiles for the occupations of sales, finance and accounting, manufacturing engineering, and research and development. The study also investigated the effectiveness of these profiles in predicting job performance. Results indicated that the criterion-related validity of personality profiles can be comparable to personality traits in some cases but may also be lower. In addition, personality profiles showed some limited evidence of incremental validity particularly for some occupation-based profiles while predicting specific job performance dimensions. Finally, the distribution of personality profiles within the top 10% of performers was also examined, and the confident profile was found to be the most represented among top performers, while the rigid profile was the least represented profile. The results of this study may inform future researchers and practitioners in relation to using personality profiles in organizational research.

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Appendix A

NB. C = Profile, C1 = Organization-based Categorical Profile 1, CPROB1 = Organization-based Continuous Profile 1, PER = Overall Performance, TAD = Thinks and Acts Decisively, LM = Leverages Mastery, IR = Innovates and Reapplies, BDCR = Builds Diverse, Collaborative Relationships, GC = Grows Capability, IT = In Touch, EC = Embraces Change, OWD = Operates with Discipline. Z added before a variable's name refers to a standardized variable in the form of z-score.

One-way ANOVA for PER

```
UNIANOVA PER BY C
  /METHOD=SSTYPE(3)
  /INTERCEPT=INCLUDE
  /POSTHOC=C (TUKEY)
  /EMMEANS=TABLES(C)
  /PRINT=ETASQ HOMOGENEITY DESCRIPTIVE
  /CRITERIA=ALPHA(.05)
  /DESIGN=C.
```

Levene's Test of Equality of Error Variances[a]

Dependent Variable: PER

F	df1	df2	Sig.
1.479	3	4133	.218

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.

a. Design: Intercept + C

Tests of Between-Subjects Effects

Dependent Variable: PER

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	37.594[a]	3	12.531	20.714	.000	.015
Intercept	1.293	1	1.293	2.138	.144	.001
C	37.594	3	12.531	20.714	.000	.015

Error	2500.338	4133	.605
Total	2539.893	4137	
Corrected Total	2537.932	4136	

a. R Squared = .015 (Adjusted R Squared = .014)

Multiple Comparisons

Dependent Variable: PER

Tukey HSD

(I) C	(J) C	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
1.000	2.000	.3439*	.06072	.000	.1878	.4999
	3.000	.0415	.03524	.641	-.0490	.1321
	4.000	.1935*	.03748	.000	.0972	.2898
2.000	1.000	-.3439*	.06072	.000	-.4999	-.1878
	3.000	-.3024*	.05528	.000	-.4444	-.1603
	4.000	-.1504*	.05673	.040	-.2962	-.0046
3.000	1.000	-.0415	.03524	.641	-.1321	.0490
	2.000	.3024*	.05528	.000	.1603	.4444
	4.000	.1520*	.02782	.000	.0805	.2235
4.000	1.000	-.1935*	.03748	.000	-.2898	-.0972
	2.000	.1504*	.05673	.040	.0046	.2962
	3.000	-.1520*	.02782	.000	-.2235	-.0805

Based on observed means.

The error term is Mean Square(Error) = .605.

*. The mean difference is significant at the .05 level.

Hierarchical regression for PER Dimensions

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT ZTAD
  /METHOD=ENTER ZO ZA ZC ZE ZN
```

/METHOD=ENTER C1 C2 C3.

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.159[a]	.025	.024	.96217789	.025	21.412	5	4131	.000
2	.164[b]	.027	.025	.96164510	.002	2.526	3	4128	.056

Coefficients[a]

		Unstandardized Coefficients		Standardized Coefficients		
Model		B	Std. Error	Beta	t	Sig.
1	(Constant)	.021	.015		1.424	.155
	Zscore(O)	-.011	.020	-.011	-.569	.570
	Zscore(A)	-.105	.018	-.103	-5.702	.000
	Zscore(C)	.026	.017	.025	1.502	.133
	Zscore(E)	.095	.019	.096	4.915	.000
	Zscore(N)	-.104	.019	-.105	-5.585	.000
2	(Constant)	.035	.042		.828	.408
	Zscore(O)	-.008	.024	-.008	-.358	.720
	Zscore(A)	-.103	.021	-.101	-4.992	.000
	Zscore(C)	.027	.018	.027	1.518	.129
	Zscore(E)	.099	.024	.100	4.101	.000
	Zscore(N)	-.111	.021	-.112	-5.166	.000
	Class 1 dummy variable	-.101	.106	-.038	-.960	.337
	Class 2 dummy variable	-.084	.089	-.019	-.944	.345
	Class 3 dummy variable	.013	.058	.007	.221	.825

a. Dependent Variable: Zscore(TAD)

```
REGRESSION
 /MISSING LISTWISE
 /STATISTICS COEFF OUTS R ANOVA CHANGE
 /CRITERIA=PIN(.05) POUT(.10)
```

```
 /NOORIGIN
 /DEPENDENT ZTAD
 /METHOD=ENTER ZO ZA ZC ZE ZN
 /METHOD=ENTER CPROB1 CPROB2 CPROB3 CPROB4.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.159[a]	.025	.024	.96217789	.025	21.412	5	4131	.000
2	.169[b]	.029	.027	.96090174	.003	4.660	3	4128	.003

```
REGRESSION
 /MISSING LISTWISE
 /STATISTICS COEFF OUTS R ANOVA CHANGE
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT ZLM
 /METHOD=ENTER ZO ZA ZC ZE ZN
 /METHOD=ENTER C1 C2 C3.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.131[a]	.017	.016	.96779280	.017	14.464	5	4131	.000
2	.141[b]	.020	.018	.96680047	.003	3.828	3	4128	.009

Coefficients[a]

		Unstandardized Coefficients		Standardized Coefficients		
Model		B	Std. Error	Beta	t	Sig.
1	(Constant)	.021	.015		1.398	.162
	Zscore(O)	-.049	.020	-.048	-2.479	.013
	Zscore(A)	-.041	.019	-.040	-2.216	.027
	Zscore(C)	.012	.017	.012	.692	.489
	Zscore(E)	.126	.019	.127	6.491	.000
	Zscore(N)	-.048	.019	-.048	-2.553	.011
2	(Constant)	.042	.043		.982	.326

Zscore(O)	-.041	.024	-.040	-1.731	.084
Zscore(A)	-.036	.021	-.035	-1.720	.085
Zscore(C)	.015	.018	.015	.847	.397
Zscore(E)	.135	.024	.136	5.572	.000
Zscore(N)	-.059	.022	-.060	-2.759	.006
Class 1 dummy variable	-.150	.106	-.056	-1.412	.158
Class 2 dummy variable	-.062	.089	-.014	-.700	.484
Class 3 dummy variable	.011	.058	.005	.185	.853

a. Dependent Variable: Zscore(LM)

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT ZLM
  /METHOD=ENTER ZO ZA ZC ZE ZN
  /METHOD=ENTER CPROB1 CPROB2 CPROB3 CPROB4.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.131[a]	.017	.016	.96779280	.017	14.464	5	4131	.000
2	.146[b]	.021	.019	.96618303	.004	5.592	3	4128	.001

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT ZIR
  /METHOD=ENTER ZO ZA ZC ZE ZN
  /METHOD=ENTER C1 C2 C3.
```

Model Summary

Model	R	R Square	Change Statistics	

			Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.194[a]	.038	.036	.95928066	.038	32.327	5	4131	.000
2	.197[b]	.039	.037	.95908208	.001	1.570	3	4128	.194

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.018	.015		1.218	.223
	Zscore(O)	.081	.020	.079	4.139	.000
	Zscore(A)	-.059	.018	-.057	-3.184	.001
	Zscore(C)	-.064	.017	-.063	-3.753	.000
	Zscore(E)	.095	.019	.096	4.942	.000
	Zscore(N)	-.101	.018	-.102	-5.455	.000
2	(Constant)	.050	.042		1.183	.237
	Zscore(O)	.095	.024	.092	4.024	.000
	Zscore(A)	-.049	.021	-.048	-2.379	.017
	Zscore(C)	-.058	.018	-.057	-3.257	.001
	Zscore(E)	.110	.024	.111	4.590	.000
	Zscore(N)	-.115	.021	-.116	-5.385	.000
	Class 1 dummy variable	-.152	.105	-.057	-1.445	.149
	Class 2 dummy variable	.025	.088	.006	.288	.773
	Class 3 dummy variable	-.022	.057	-.011	-.387	.699

a. Dependent Variable: Zscore(IR)

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT ZIR
  /METHOD=ENTER ZO ZA ZC ZE ZN
  /METHOD=ENTER CPROB1 CPROB2 CPROB3 CPROB4.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.194[a]	.038	.036	.95928066	.038	32.327	5	4131	.000
2	.199[b]	.040	.038	.95859228	.002	2.978	3	4128	.030

```
REGRESSION
 /MISSING LISTWISE
 /STATISTICS COEFF OUTS R ANOVA CHANGE
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT ZLeads
 /METHOD=ENTER ZO ZA ZC ZE ZN
 /METHOD=ENTER C1 C2 C3.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.188[a]	.035	.034	.96390230	.035	30.398	5	4131	.000
2	.191[b]	.037	.035	.96370900	.001	1.552	3	4128	.199

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.018	.015		1.185	.236
	Zscore(O)	-.106	.020	-.103	-5.408	.000
	Zscore(A)	.032	.018	.031	1.719	.086
	Zscore(C)	.020	.017	.020	1.186	.236
	Zscore(E)	.147	.019	.147	7.588	.000
	Zscore(N)	-.086	.019	-.086	-4.608	.000
2	(Constant)	.047	.043		1.110	.267
	Zscore(O)	-.094	.024	-.091	-3.963	.000
	Zscore(A)	.040	.021	.039	1.942	.052
	Zscore(C)	.025	.018	.025	1.406	.160

Zscore(E)	.160	.024	.161	6.632	.000
Zscore(N)	-.098	.021	-.099	-4.588	.000
Class 1 dummy variable	-.142	.106	-.053	-1.346	.178
Class 2 dummy variable	.007	.089	.002	.075	.940
Class 3 dummy variable	-.018	.058	-.009	-.310	.757

a. Dependent Variable: Zscore(Leads)

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT ZLeads
  /METHOD=ENTER ZO ZA ZC ZE ZN
  /METHOD=ENTER CPROB1 CPROB2 CPROB3 CPROB4.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.188[a]	.035	.034	.96390230	.035	30.398	5	4131	.000
2	.193[b]	.037	.035	.96346212	.002	2.259	3	4128	.080

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT ZBDCR
  /METHOD=ENTER ZO ZA ZC ZE ZN
  /METHOD=ENTER C1 C2 C3.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change

1	.210[a]	.044	.043	.95834450	.044	38.124	5	4131	.000
2	.212[b]	.045	.043	.95817728	.001	1.481	3	4128	.218

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.016	.015		1.056	.291
	Zscore(O)	-.097	.020	-.094	-4.980	.000
	Zscore(A)	.219	.018	.213	11.911	.000
	Zscore(C)	-.010	.017	-.010	-.571	.568
	Zscore(E)	.028	.019	.028	1.468	.142
	Zscore(N)	-.031	.018	-.031	-1.666	.096
2	(Constant)	.049	.042		1.165	.244
	Zscore(O)	-.083	.024	-.081	-3.534	.000
	Zscore(A)	.229	.021	.223	11.115	.000
	Zscore(C)	-.004	.018	-.004	-.227	.820
	Zscore(E)	.043	.024	.043	1.800	.072
	Zscore(N)	-.045	.021	-.045	-2.095	.036
	Class 1 dummy variable	-.151	.105	-.056	-1.436	.151
	Class 2 dummy variable	.020	.088	.004	.221	.825
	Class 3 dummy variable	-.025	.057	-.013	-.440	.660

a. Dependent Variable: Zscore(BDCR)

```
REGRESSION
 /MISSING LISTWISE
 /STATISTICS COEFF OUTS R ANOVA CHANGE
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT ZBDCR
 /METHOD=ENTER ZO ZA ZC ZE ZN
 /METHOD=ENTER CPROB1 CPROB2 CPROB3 CPROB4.
```

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics R Square Change	F Change	df1	df2	Sig. F Change
1	.210[a]	.044	.043	.95834450	.044	38.124	5	4131	.000
2	.213[b]	.045	.044	.95803331	.001	1.895	3	4128	.128

```
REGRESSION
 /MISSING LISTWISE
 /STATISTICS COEFF OUTS R ANOVA CHANGE
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT ZGC
 /METHOD=ENTER ZO ZA ZC ZE ZN
 /METHOD=ENTER C1 C2 C3.
```

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics R Square Change	F Change	df1	df2	Sig. F Change
1	.123[a]	.015	.014	.96777344	.015	12.613	5	4131	.000
2	.128[b]	.016	.014	.96750916	.001	1.752	3	4128	.154

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.022	.015		1.438	.151
	Zscore(O)	-.012	.020	-.012	-.609	.543
	Zscore(A)	-.051	.019	-.050	-2.770	.006
	Zscore(C)	.066	.017	.066	3.860	.000
	Zscore(E)	.061	.019	.062	3.136	.002
	Zscore(N)	-.066	.019	-.067	-3.564	.000
2	(Constant)	-.009	.043		-.215	.830
	Zscore(O)	-.016	.024	-.016	-.670	.503
	Zscore(A)	-.055	.021	-.054	-2.652	.008
	Zscore(C)	.064	.018	.063	3.541	.000
	Zscore(E)	.055	.024	.056	2.279	.023

Zscore(N)	-.066	.022	-.066	-3.053	.002
Class 1 dummy variable	-.004	.106	-.001	-.035	.972
Class 2 dummy variable	-.023	.089	-.005	-.257	.797
Class 3 dummy variable	.069	.058	.035	1.189	.235

a. Dependent Variable: Zscore(GC)

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT ZGC
  /METHOD=ENTER ZO ZA ZC ZE ZN
  /METHOD=ENTER CPROB1 CPROB2 CPROB3 CPROB4.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.123[a]	.015	.014	.96777344	.015	12.613	5	4131	.000
2	.132[b]	.017	.016	.96694778	.002	3.353	3	4128	.018

```
REGRESSION
 /MISSING LISTWISE
 /STATISTICS COEFF OUTS R ANOVA CHANGE
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT ZIT
 /METHOD=ENTER ZO ZA ZC ZE ZN
 /METHOD=ENTER C1 C2 C3.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.106[a]	.011	.010	.96901011	.011	9.459	5	4131	.000
2	.114[b]	.013	.011	.96849456	.002	2.466	3	4128	.060

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.021	.015		1.401	.161
	Zscore(O)	-.039	.020	-.038	-1.977	.048
	Zscore(A)	.003	.019	.003	.183	.855
	Zscore(C)	.005	.017	.005	.308	.758
	Zscore(E)	.067	.019	.068	3.445	.001
	Zscore(N)	-.068	.019	-.069	-3.667	.000
2	(Constant)	.060	.043		1.402	.161
	Zscore(O)	-.016	.024	-.016	-.673	.501
	Zscore(A)	.018	.021	.018	.888	.375
	Zscore(C)	.014	.018	.014	.766	.444
	Zscore(E)	.090	.024	.091	3.722	.000
	Zscore(N)	-.089	.022	-.090	-4.121	.000
	Class 1 dummy variable	-.202	.106	-.075	-1.900	.058
	Class 2 dummy variable	.109	.089	.025	1.223	.221
	Class 3 dummy variable	-.031	.058	-.016	-.534	.594

a. Dependent Variable: Zscore(IT)

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT ZIT
  /METHOD=ENTER ZO ZA ZC ZE ZN
  /METHOD=ENTER CPROB1 CPROB2 CPROB3 CPROB4.
```

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics R Square Change	F Change	df1	df2	Sig. F Change
1	.106[a]	.011	.010	.96901011	.011	9.459	5	4131	.000
2	.115[b]	.013	.011	.96842609	.002	2.661	3	4128	.046

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT ZEC
  /METHOD=ENTER ZO ZA ZC ZE ZN
  /METHOD=ENTER C1 C2 C3.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.157[a]	.025	.024	.96613247	.025	20.999	5	4131	.000
2	.161[b]	.026	.024	.96598179	.001	1.430	3	4128	.232

Coefficients[a]

		Unstandardized Coefficients		Standardized Coefficients		
Model		B	Std. Error	Beta	t	Sig.
1	(Constant)	.022	.015		1.447	.148
	Zscore(O)	-.026	.020	-.025	-1.327	.185
	Zscore(A)	-.013	.019	-.013	-.699	.484
	Zscore(C)	-.006	.017	-.006	-.377	.706
	Zscore(E)	.075	.019	.076	3.863	.000
	Zscore(N)	-.123	.019	-.124	-6.628	.000
2	(Constant)	-.003	.043		-.065	.949
	Zscore(O)	-.033	.024	-.032	-1.390	.165
	Zscore(A)	-.018	.021	-.018	-.869	.385
	Zscore(C)	-.009	.018	-.009	-.526	.599
	Zscore(E)	.067	.024	.068	2.777	.006
	Zscore(N)	-.121	.021	-.122	-5.623	.000
	Class 1 dummy variable	.005	.106	.002	.051	.959
	Class 2 dummy variable	-.072	.089	-.017	-.813	.416

	Class 3 dummy variable	.058	.058	.030	1.011	.312

a. Dependent Variable: Zscore(EC)

```
REGRESSION
 /MISSING LISTWISE
 /STATISTICS COEFF OUTS R ANOVA CHANGE
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT ZEC
 /METHOD=ENTER ZO ZA ZC ZE ZN
 /METHOD=ENTER CPROB1 CPROB2 CPROB3 CPROB4.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.157[a]	.025	.024	.96613247	.025	20.999	5	4131	.000
2	.165[b]	.027	.025	.96532502	.002	3.305	3	4128	.019

```
REGRESSION
 /MISSING LISTWISE
 /STATISTICS COEFF OUTS R ANOVA CHANGE
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT ZOWD
 /METHOD=ENTER ZO ZA ZC ZE ZN
 /METHOD=ENTER C1 C2 C3.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.187[a]	.035	.034	.95506694	.035	29.901	5	4131	.000
2	.188[b]	.035	.034	.95515464	.001	.747	3	4128	.524

Coefficients[a]

		Unstandardized Coefficients		Standardized Coefficients		
Model		B	Std. Error	Beta	t	Sig.
1	(Constant)	.023	.015		1.534	.125

	Zscore(O)	-.075	.019	-.073	-3.853	.000
	Zscore(A)	-.109	.018	-.107	-5.956	.000
	Zscore(C)	.134	.017	.134	7.939	.000
	Zscore(E)	.116	.019	.117	6.035	.000
	Zscore(N)	-.064	.018	-.065	-3.473	.001
2	(Constant)	.010	.042		.243	.808
	Zscore(O)	-.074	.024	-.073	-3.161	.002
	Zscore(A)	-.109	.020	-.107	-5.334	.000
	Zscore(C)	.134	.018	.133	7.540	.000
	Zscore(E)	.116	.024	.117	4.824	.000
	Zscore(N)	-.066	.021	-.067	-3.100	.002
	Class 1 dummy variable	-.025	.105	-.009	-.240	.810
	Class 2 dummy variable	.003	.088	.001	.029	.977
	Class 3 dummy variable	.034	.057	.018	.595	.552

a. Dependent Variable: Zscore(OWD)

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT ZOWD
  /METHOD=ENTER ZO ZA ZC ZE ZN
  /METHOD=ENTER CPROB1 CPROB2 CPROB3 CPROB4.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.187[a]	.035	.034	.95506694	.035	29.901	5	4131	.000
2	.190[b]	.036	.034	.95484116	.001	1.651	3	4128	.175

Appendix B

NB. C = Profile, TAD = Thinks and Acts Decisively, CBD = Sales, F&A = Finance and Accounting, CMK = Market Research, ER = External Relations, HR = Human Resources, IDS = Information Technology, MKT = Marketing, PS = Manufacturing Engineering, R&D = Research and Development. Z added before a variable's name refers to a standardized variable in the form of z-score.

Post Hoc Tests

Occupations

Multiple Comparisons

Dependent Variable: Zscore(TAD)

Tukey HSD

(I) Occup.	(J) Occup.	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
CBD	CMK	-.3253413*	0.0835	0.005	-0.5943	-0.0564
	Design	0.09871	0.12842	1	-0.3149	0.51229
	ER	-0.034	0.09528	1	-0.3409	0.27281
	F&A	-.2285462*	0.05885	0.005	-0.4181	-0.039
	HR	-0.134	0.09236	0.935	-0.4315	0.16339
	IDS	-0.2	0.07141	0.158	-0.43	0.02994
	Legal	-0.0824	0.17948	1	-0.6604	0.49563
	MKT	-.3581466*	0.06545	0	-0.5689	-0.1474

	PS	-.1533314*	0.04637	0.038	-0.3027	-0.004
	R&D	-.2504188*	0.04847	0	-0.4065	-0.0943
CMK	CBD	.3253413*	0.0835	0.005	0.05642	0.59427
	Design	0.42405	0.14459	0.113	-0.0416	0.88969
	ER	0.29131	0.11615	0.3	-0.0828	0.66537
	F&A	0.0968	0.08875	0.992	-0.189	0.38261
	HR	0.1913	0.11377	0.845	-0.1751	0.55768
	IDS	0.12532	0.09753	0.971	-0.1888	0.43941
	Legal	0.24297	0.19138	0.974	-0.3734	0.8593
	MKT	-0.0328	0.09325	1	-0.3331	0.26752
	PS	0.17201	0.08102	0.561	-0.0889	0.43292
	R&D	0.07492	0.08223	0.998	-0.1899	0.33975
Design	CBD	-0.0987	0.12842	1	-0.5123	0.31488
	CMK	-0.4241	0.14459	0.113	-0.8897	0.04159
	ER	-0.1327	0.15169	0.999	-0.6213	0.35578
	F&A	-0.3273	0.13189	0.316	-0.752	0.09751
	HR	-0.2328	0.14987	0.901	-0.7154	0.24992
	IDS	-0.2987	0.13795	0.53	-0.743	0.14555
	Legal	-0.1811	0.21481	0.999	-0.8729	0.51072
	MKT	-.4568557*	0.13497	0.03	-0.8915	-0.0222
	PS	-0.252	0.12682	0.658	-0.6605	0.15638
	R&D	-0.3491	0.1276	0.184	-0.7601	0.0618
ER	CBD	0.03403	0.09528	1	-0.2728	0.34087
	CMK	-0.2913	0.11615	0.3	-0.6654	0.08275
	Design	0.13274	0.15169	0.999	-0.3558	0.62126
	F&A	-0.1945	0.09991	0.686	-0.5163	0.12723
	HR	-0.1	0.12267	0.999	-0.4951	0.29504

	IDS	-0.166	0.10778	0.906	-0.5131	0.18111
	Legal	-0.0483	0.1968	1	-0.6821	0.58545
	MKT	-0.3241	0.10393	0.068	-0.6588	0.01058
	PS	-0.1193	0.0931	0.972	-0.4191	0.18054
	R&D	-0.2164	0.09417	0.435	-0.5196	0.08687
F&A	CBD	.2285462*	0.05885	0.005	0.03902	0.41807
	CMK	-0.0968	0.08875	0.992	-0.3826	0.18902
	Design	0.32726	0.13189	0.316	-0.0975	0.75202
	ER	0.19452	0.09991	0.686	-0.1272	0.51627
	HR	0.0945	0.09712	0.997	-0.2183	0.40729
	IDS	0.02852	0.07747	1	-0.221	0.27803
	Legal	0.14617	0.18198	0.999	-0.4399	0.73223
	MKT	-0.1296	0.07202	0.781	-0.3615	0.10233
	PS	0.07521	0.05526	0.958	-0.1028	0.25319
	R&D	-0.0219	0.05703	1	-0.2055	0.1618
HR	CBD	0.13404	0.09236	0.935	-0.1634	0.43148
	CMK	-0.1913	0.11377	0.845	-0.5577	0.17509
	Design	0.23275	0.14987	0.901	-0.2499	0.71542
	ER	0.10001	0.12267	0.999	-0.295	0.49507
	F&A	-0.0945	0.09712	0.997	-0.4073	0.21829
	IDS	-0.066	0.10521	1	-0.4048	0.27284
	Legal	0.05167	0.1954	1	-0.5776	0.68096
	MKT	-0.2241	0.10126	0.495	-0.5502	0.10199
	PS	-0.0193	0.09011	1	-0.3095	0.27092
	R&D	-0.1164	0.09121	0.973	-0.4101	0.17736
IDS	CBD	0.20003	0.07141	0.158	-0.0299	0.42999
	CMK	-0.1253	0.09753	0.971	-0.4394	0.18877
	Design	0.29873	0.13795	0.53	-0.1455	0.74301
	ER	0.166	0.10778	0.906	-0.1811	0.5131
	F&A	-0.0285	0.07747	1	-0.278	0.22098
	HR	0.06598	0.10521	1	-0.2728	0.4048
	Legal	0.11765	0.18642	1	-0.4827	0.718
	MKT	-0.1581	0.08259	0.708	-0.4241	0.10787

	PS	0.04669	0.06848	1	-0.1738	0.26723
	R&D	-0.0504	0.06991	1	-0.2755	0.17476
Legal	CBD	0.08237	0.17948	1	-0.4956	0.66038
	CMK	-0.243	0.19138	0.974	-0.8593	0.37336
	Design	0.18108	0.21481	0.999	-0.5107	0.87289
	ER	0.04834	0.1968	1	-0.5854	0.68213
	F&A	-0.1462	0.18198	0.999	-0.7322	0.43988
	HR	-0.0517	0.1954	1	-0.681	0.57762
	IDS	-0.1177	0.18642	1	-0.718	0.4827
	MKT	-0.2758	0.18422	0.921	-0.869	0.31749
	PS	-0.071	0.17833	1	-0.6453	0.50336
	R&D	-0.168	0.17889	0.998	-0.7442	0.40806
MKT	CBD	.3581466*	0.06545	0	0.14738	0.56891
	CMK	0.03281	0.09325	1	-0.2675	0.33313
	Design	.4568557*	0.13497	0.03	0.0222	0.89151
	ER	0.32412	0.10393	0.068	-0.0106	0.65882
	F&A	0.1296	0.07202	0.781	-0.1023	0.36153
	HR	0.2241	0.10126	0.495	-0.102	0.5502
	IDS	0.15812	0.08259	0.708	-0.1079	0.42412
	Legal	0.27577	0.18422	0.921	-0.3175	0.86904
	PS	.2048152*	0.06224	0.04	0.00438	0.40525
	R&D	0.10773	0.06381	0.842	-0.0978	0.31324
PS	CBD	.1533314*	0.04637	0.038	0.00399	0.30268
	CMK	-0.172	0.08102	0.561	-0.4329	0.0889
	Design	0.25204	0.12682	0.658	-0.1564	0.66046
	ER	0.1193	0.0931	0.972	-0.1805	0.41915
	F&A	-0.0752	0.05526	0.958	-0.2532	0.10276
	HR	0.01929	0.09011	1	-0.2709	0.30949
	IDS	-0.0467	0.06848	1	-0.2672	0.17384

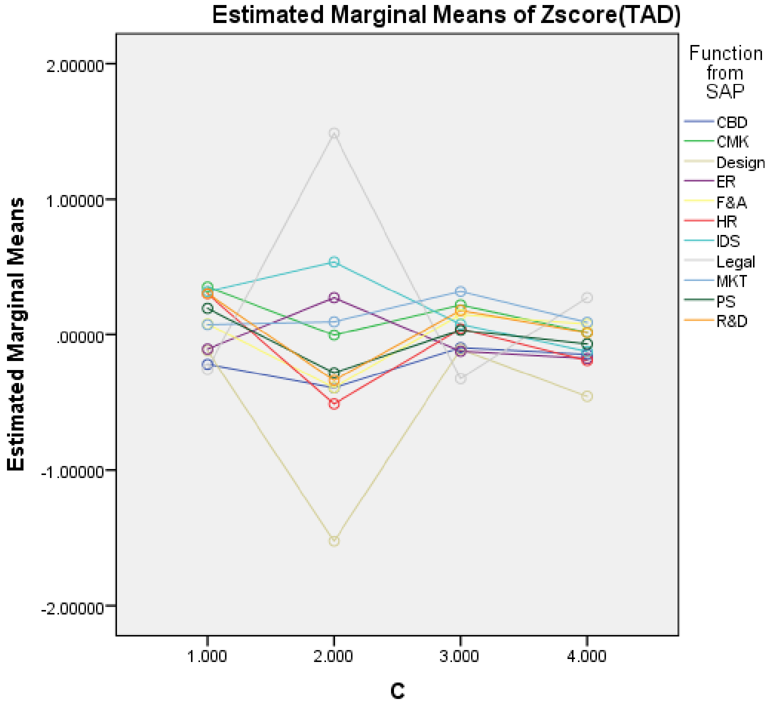
	Legal	0.07096	0.17833	1	-0.5034	0.64528
	MKT	-.2048152*	0.06224	0.04	-0.4053	-0.0044
	R&D	-0.0971	0.04404	0.502	-0.2389	0.04475
R&D	CBD	.2504188*	0.04847	0	0.09433	0.40651
	CMK	-0.0749	0.08223	0.998	-0.3398	0.18991
	Design	0.34913	0.1276	0.184	-0.0618	0.76006
	ER	0.21639	0.09417	0.435	-0.0869	0.51965
	F&A	0.02187	0.05703	1	-0.1618	0.20554
	HR	0.11638	0.09121	0.973	-0.1774	0.41011
	IDS	0.05039	0.06991	1	-0.1748	0.27555
	Legal	0.16805	0.17889	0.998	-0.4081	0.74416
	MKT	-0.1077	0.06381	0.842	-0.3132	0.09778
	PS	0.09709	0.04404	0.502	-0.0447	0.23892

Based on observed means.

The error term is Mean Square(Error) = .928.

$^{*}p < .05$, $^{**}p < .01$ $^{***}p < .001$.

Profiles Plots


Estimated Marginal Means of Zscore(TAD)
Estimated Marginal Means
2.00000
1.00000
.00000
-1.00000
-2.00000
1.000
2.000
3.000
4.000
C
Function from SAP
CBD
CMK
Design
ER
F&A
HR
IDS
Legal
MKT
PS
R&D

Appendix C

NB. C = Profile, PER = Overall Performance, TAD = Thinks and Acts Decisively, LM = Leverages Mastery, IR = Innovates and Reapplies, BDCR = Builds Diverse, Collaborative Relationships, GC = Grows Capability, IT = In Touch, EC = Embraces Change, OWD = Operates with Discipline, CBD = Sales, F&A = Finance and Accounting, CMK = Market Research, ER = External Relations, HR = Human Resources, IDS = Information Technology, MKT = Marketing, PS = Manufacturing Engineering, R&D = Research and Development. Z added before a variable's name refers to a standardized variable in the form of z-score.

```
UNIANOVA ZTAD BY C Occupation
 /METHOD=SSTYPE(3)
 /INTERCEPT=INCLUDE
 /POSTHOC=C Occupation(TUKEY)
 /PLOT=PROFILE(C*Occupation)
 /EMMEANS=TABLES(C)
 /EMMEANS=TABLES(Occupation)
 /EMMEANS=TABLES(C*Occupation)
 /PRINT=ETASQ HOMOGENEITY DESCRIPTIVE
 /CRITERIA=ALPHA(.05)
 /DESIGN=C Occupation C*Occupation.
```

Levene's Test of Equality of Error Variances[a]

Dependent Variable: Zscore(TAD)

F	df1	df2	Sig.
1.170	43	4093	.208

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.[a]

a. Design: Intercept + C + Occupation + C * Occupation

Tests of Between-Subjects Effects

Dependent Variable: Zscore(TAD)

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared

Corrected Model	125.379[a]	43	2.916	3.142	.000	.032
Intercept	.064	1	.064	.069	.793	.000
C	4.373	3	1.458	1.571	.194	.001
Occupation	32.687	10	3.269	3.522	.000	.009
C * Occupation	41.636	30	1.388	1.496	.040	.011
Error	3798.158	4093	.928			
Total	3925.534	4137				
Corrected Total	3923.538	4136				

a. R Squared = .032 (Adjusted R Squared = .022)

Post Hoc Tests (Occupations)

Multiple Comparisons

Dependent Variable: Zscore(TAD)

Tukey HSD

		Mean Difference			95% Confidence Interval	
(I) Occup.	(J) Occup.	(I-J)	Std. Error	Sig.	Lower Bound	Upper Bound
CBD	CMK	-.3253413*	.08350440	.005	-.5942664	-.0564163
	Design	.0987091	.12842306	1.000	-.3148761	.5122942
	ER	-.0340299	.09527839	1.000	-.3408730	.2728132
	F&A	-.2285462*	.05885063	.005	-.4180741	-.0390184
	HR	-.1340434	.09235623	.935	-.4314757	.1633889
	IDS	-.2000254	.07140542	.158	-.4299858	.0299351
	Legal	-.0823726	.17947729	1.000	-.6603774	.4956321
	MKT	-.3581466*	.06544518	.000	-.5689121	-.1473811
	PS	-.1533314*	.04637307	.038	-.3026754	-.0039874
	R&D	-.2504188*	.04846684	.000	-.4065057	-.0943318
CMK	CBD	.3253413*	.08350440	.005	.0564163	.5942664
	Design	.4240504	.14458757	.113	-.0415923	.8896932
	ER	.2913115	.11615099	.300	-.0827516	.6653745
	F&A	.0967951	.08874953	.992	-.1890218	.3826121
	HR	.1912980	.11376623	.845	-.1750850	.5576809
	IDS	.1253160	.09752854	.971	-.1887737	.4394057
	Legal	.2429687	.19137706	.974	-.3733592	.8592966

	MKT	-.0328052	.09325317	1.000	-.3331261	.2675156
	PS	.1720100	.08101570	.561	-.0889003	.4329202
	R&D	.0749226	.08223209	.998	-.1899050	.3397502
Design	CBD	-.0987091	.12842306	1.000	-.5122942	.3148761
	CMK	-.4240504	.14458757	.113	-.8896932	.0415923
	ER	-.1327390	.15169229	.999	-.6212625	.3557845
	F&A	-.3272553	.13189381	.316	-.7520180	.0975074
	HR	-.2327525	.14987413	.901	-.7154206	.2499156
	IDS	-.2987344	.13795403	.530	-.7430140	.1455451
	Legal	-.1810817	.21481312	.999	-.8728852	.5107217
	MKT	-.4568557*	.13496538	.030	-.8915103	-.0222011
	PS	-.2520405	.12681893	.658	-.6604595	.1563786
	R&D	-.3491279	.12759943	.184	-.7600605	.0618048
ER	CBD	.0340299	.09527839	1.000	-.2728132	.3408730
	CMK	-.2913115	.11615099	.300	-.6653745	.0827516
	Design	.1327390	.15169229	.999	-.3557845	.6212625
	F&A	-.1945163	.09990729	.686	-.5162667	.1272341
	HR	-.1000135	.12266924	.999	-.4950685	.2950415
	IDS	-.1659955	.10778128	.906	-.5131040	.1811130
	Legal	-.0483428	.19679982	1.000	-.6821345	.5854490
	MKT	-.3241167	.10392854	.068	-.6588175	.0105841
	PS	-.1193015	.09310495	.972	-.4191450	.1805420
	R&D	-.2163889	.09416530	.435	-.5196473	.0868695
F&A	CBD	.2285462*	.05885063	.005	.0390184	.4180741
	CMK	-.0967951	.08874953	.992	-.3826121	.1890218
	Design	.3272553	.13189381	.316	-.0975074	.7520180
	ER	.1945163	.09990729	.686	-.1272341	.5162667
	HR	.0945028	.09712450	.997	-.2182856	.4072912
	IDS	.0285208	.07747406	1.000	-.2209836	.2780252
	Legal	.1461736	.18197690	.999	-.4398812	.7322283
	MKT	-.1296004	.07201782	.781	-.3615331	.1023323
	PS	.0752148	.05526261	.958	-.1027579	.2531875
	R&D	-.0218726	.05703095	1.000	-.2055402	.1617950

HR	CBD	.1340434	.09235623	.935	-.1633889	.4314757
	CMK	-.1912980	.11376623	.845	-.5576809	.1750850
	Design	.2327525	.14987413	.901	-.2499156	.7154206
	ER	.1000135	.12266924	.999	-.2950415	.4950685
	F&A	-.0945028	.09712450	.997	-.4072912	.2182856
	IDS	-.0659820	.10520697	1.000	-.4047999	.2728360
	Legal	.0516708	.19540181	1.000	-.5776188	.6809603
	MKT	-.2241032	.10125632	.495	-.5501982	.1019917
	PS	-.0192880	.09011233	1.000	-.3094938	.2709179
	R&D	-.1163754	.09120749	.973	-.4101082	.1773574
IDS	CBD	.2000254	.07140542	.158	-.0299351	.4299858
	CMK	-.1253160	.09752854	.971	-.4394057	.1887737
	Design	.2987344	.13795403	.530	-.1455451	.7430140
	ER	.1659955	.10778128	.906	-.1811130	.5131040
	F&A	-.0285208	.07747406	1.000	-.2780252	.2209836
	HR	.0659820	.10520697	1.000	-.2728360	.4047999
	Legal	.1176527	.18641602	1.000	-.4826981	.7180036
	MKT	-.1581212	.08259482	.708	-.4241170	.1078745
	PS	.0466940	.06847842	1.000	-.1738401	.2672280
	R&D	-.0503934	.06991328	1.000	-.2755484	.1747616
Legal	CBD	.0823726	.17947729	1.000	-.4956321	.6603774
	CMK	-.2429687	.19137706	.974	-.8592966	.3733592
	Design	.1810817	.21481312	.999	-.5107217	.8728852
	ER	.0483428	.19679982	1.000	-.5854490	.6821345
	F&A	-.1461736	.18197690	.999	-.7322283	.4398812
	HR	-.0516708	.19540181	1.000	-.6809603	.5776188
	IDS	-.1176527	.18641602	1.000	-.7180036	.4826981
	MKT	-.2757740	.18421528	.921	-.8690374	.3174895
	PS	-.0709587	.17833300	1.000	-.6452783	.5033608
	R&D	-.1680462	.17888888	.998	-.7441559	.4080636
MKT	CBD	.3581466*	.06544518	.000	.1473811	.5689121
	CMK	.0328052	.09325317	1.000	-.2675156	.3331261
	Design	.4568557*	.13496538	.030	.0222011	.8915103

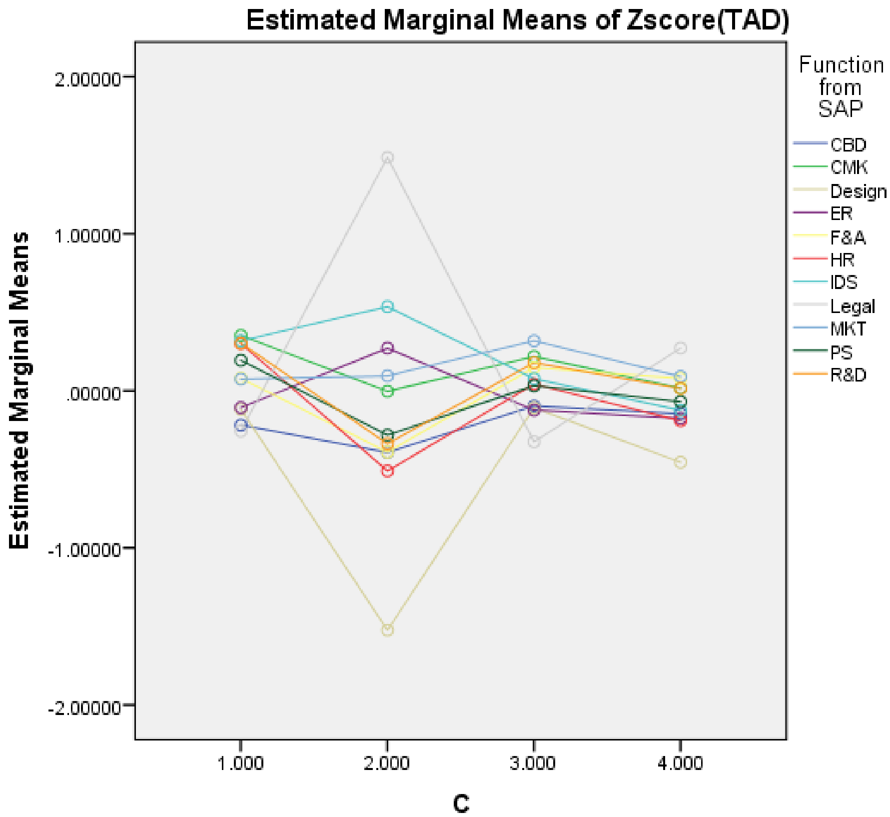
	ER	.3241167	.10392854	.068	-.0105841	.6588175
	F&A	.1296004	.07201782	.781	-.1023323	.3615331
	HR	.2241032	.10125632	.495	-.1019917	.5501982
	IDS	.1581212	.08259482	.708	-.1078745	.4241170
	Legal	.2757740	.18421528	.921	-.3174895	.8690374
	PS	.2048152*	.06223851	.040	.0043767	.4052537
	R&D	.1077278	.06381383	.842	-.0977840	.3132396
PS	CBD	.1533314*	.04637307	.038	.0039874	.3026754
	CMK	-.1720100	.08101570	.561	-.4329202	.0889003
	Design	.2520405	.12681893	.658	-.1563786	.6604595
	ER	.1193015	.09310495	.972	-.1805420	.4191450
	F&A	-.0752148	.05526261	.958	-.2531875	.1027579
	HR	.0192880	.09011233	1.000	-.2709179	.3094938
	IDS	-.0466940	.06847842	1.000	-.2672280	.1738401
	Legal	.0709587	.17833300	1.000	-.5033608	.6452783
	MKT	-.2048152*	.06223851	.040	-.4052537	-.0043767
	R&D	-.0970874	.04404082	.502	-.2389204	.0447456
R&D	CBD	.2504188*	.04846684	.000	.0943318	.4065057
	CMK	-.0749226	.08223209	.998	-.3397502	.1899050
	Design	.3491279	.12759943	.184	-.0618048	.7600605
	ER	.2163889	.09416530	.435	-.0868695	.5196473
	F&A	.0218726	.05703095	1.000	-.1617950	.2055402
	HR	.1163754	.09120749	.973	-.1773574	.4101082
	IDS	.0503934	.06991328	1.000	-.1747616	.2755484
	Legal	.1680462	.17888888	.998	-.4080636	.7441559
	MKT	-.1077278	.06381383	.842	-.3132396	.0977840
	PS	.0970874	.04404082	.502	-.0447456	.2389204

Based on observed means.

The error term is Mean Square(Error) = .928.

*. The mean difference is significant at the .05 level.

Profile Plots




```
UNIANOVA ZLM BY C Occupation
  /METHOD=SSTYPE(3)
  /INTERCEPT=INCLUDE
  /POSTHOC=C Occupation(TUKEY)
  /PLOT=PROFILE(C*Occupation)
  /EMMEANS=TABLES(C)
  /EMMEANS=TABLES(Occupation)
  /EMMEANS=TABLES(C*Occupation)
  /PRINT=ETASQ HOMOGENEITY DESCRIPTIVE
  /CRITERIA=ALPHA(.05)
  /DESIGN=C Occupation C*Occupation.
```

Levene's Test of Equality of Error Variances[a]

Dependent Variable: Zscore(LM)

F	df1	df2	Sig.
.705	43	4093	.926

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.[a]

a. Design: Intercept + C + Occupation + C * Occupation

Tests of Between-Subjects Effects

Dependent Variable: Zscore(LM)

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	84.894[a]	43	1.974	2.098	.000	.022
Intercept	.205	1	.205	.218	.641	.000
C	6.595	3	2.198	2.336	.072	.002
Occupation	22.222	10	2.222	2.361	.009	.006
C * Occupation	35.803	30	1.193	1.268	.150	.009
Error	3852.031	4093	.941			
Total	3938.862	4137				
Corrected Total	3936.925	4136				

a. R Squared = .022 (Adjusted R Squared = .011)

```
UNIANOVA ZIR BY C Occupation
 /METHOD=SSTYPE(3)
 /INTERCEPT=INCLUDE
 /POSTHOC=C Occupation(TUKEY)
 /PLOT=PROFILE(C*Occupation)
 /EMMEANS=TABLES(C)
 /EMMEANS=TABLES(Occupation)
 /EMMEANS=TABLES(C*Occupation)
 /PRINT=ETASQ HOMOGENEITY DESCRIPTIVE
 /CRITERIA=ALPHA(.05)
 /DESIGN=C Occupation C*Occupation.
```

Levene's Test of Equality of Error Variances[a]

Dependent Variable: Zscore(IR)

F	df1	df2	Sig.
1.015	43	4093	.445

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.[a]

a. Design: Intercept + C + Occupation + C * Occupation

Tests of Between-Subjects Effects

Dependent Variable: Zscore(IR)

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	199.427[a]	43	4.638	5.061	.000	.050
Intercept	.065	1	.065	.071	.790	.000
C	32.379	3	10.793	11.778	.000	.009
Occupation	50.224	10	5.022	5.481	.000	.013
C * Occupation	38.293	30	1.276	1.393	.076	.010
Error	3750.739	4093	.916			
Total	3951.843	4137				
Corrected Total	3950.166	4136				

a. R Squared = .050 (Adjusted R Squared = .041)

```
UNIANOVA ZLeads BY C Occupation
 /METHOD=SSTYPE(3)
 /INTERCEPT=INCLUDE
 /POSTHOC=C Occupation(TUKEY)
 /PLOT=PROFILE(C*Occupation)
 /EMMEANS=TABLES(C)
 /EMMEANS=TABLES(Occupation)
 /EMMEANS=TABLES(C*Occupation)
 /PRINT=ETASQ HOMOGENEITY DESCRIPTIVE
 /CRITERIA=ALPHA(.05)
 /DESIGN=C Occupation C*Occupation.
```

Levene's Test of Equality of Error Variances[a]

Dependent Variable: Zscore(Leads)

F	df1	df2	Sig.
1.034	43	4093	.410

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.[a]

a. Design: Intercept + C + Occupation + C * Occupation

Tests of Between-Subjects Effects

Dependent Variable: Zscore(Leads)

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	118.152[a]	43	2.748	2.913	.000	.030
Intercept	.002	1	.002	.002	.967	.000
C	17.051	3	5.684	6.025	.000	.004
Occupation	19.078	10	1.908	2.022	.027	.005
C * Occupation	34.671	30	1.156	1.225	.186	.009
Error	3861.206	4093	.943			
Total	3980.976	4137				
Corrected Total	3979.359	4136				

a. R Squared = .030 (Adjusted R Squared = .019)

```
UNIANOVA ZBDCR BY C Occupation
 /METHOD=SSTYPE(3)
 /INTERCEPT=INCLUDE
 /POSTHOC=C Occupation(TUKEY)
 /PLOT=PROFILE(C*Occupation)
 /EMMEANS=TABLES(C)
 /EMMEANS=TABLES(Occupation)
 /EMMEANS=TABLES(C*Occupation)
 /PRINT=ETASQ HOMOGENEITY DESCRIPTIVE
 /CRITERIA=ALPHA(.05)
 /DESIGN=C Occupation C*Occupation.
```

Levene's Test of Equality of Error Variances[a]

Dependent Variable: Zscore(BDCR)

F	df1	df2	Sig.
1.059	43	4093	.367

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.[a]

a. Design: Intercept + C + Occupation + C * Occupation

Tests of Between-Subjects Effects

Dependent Variable: Zscore(BDCR)

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	98.789[a]	43	2.297	2.430	.000	.025
Intercept	.674	1	.674	.713	.399	.000
C	12.019	3	4.006	4.237	.005	.003
Occupation	16.657	10	1.666	1.762	.062	.004
C * Occupation	20.949	30	.698	.738	.848	.005
Error	3870.291	4093	.946			
Total	3970.618	4137				
Corrected Total	3969.081	4136				

a. R Squared = .025 (Adjusted R Squared = .015)

```
UNIANOVA ZGC BY C Occupation
 /METHOD=SSTYPE(3)
 /INTERCEPT=INCLUDE
 /POSTHOC=C Occupation(TUKEY)
 /PLOT=PROFILE(C*Occupation)
 /EMMEANS=TABLES(C)
 /EMMEANS=TABLES(Occupation)
 /EMMEANS=TABLES(C*Occupation)
 /PRINT=ETASQ HOMOGENEITY DESCRIPTIVE
 /CRITERIA=ALPHA(.05)
 /DESIGN=C Occupation C*Occupation.
```

Levene's Test of Equality of Error Variances[a]

Dependent Variable: Zscore(GC)

F	df1	df2	Sig.
.968	43	4093	.532

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.[a]

a. Design: Intercept + C + Occupation + C * Occupation

Tests of Between-Subjects Effects

Dependent Variable: Zscore(GC)

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	93.786[a]	43	2.181	2.328	.000	.024
Intercept	.001	1	.001	.001	.974	.000
C	12.077	3	4.026	4.297	.005	.003
Occupation	25.607	10	2.561	2.733	.002	.007
C * Occupation	28.333	30	.944	1.008	.454	.007
Error	3834.312	4093	.937			
Total	3930.355	4137				
Corrected Total	3928.098	4136				

a. R Squared = .024 (Adjusted R Squared = .014)

```
UNIANOVA ZIT BY C Occupation
 /METHOD=SSTYPE(3)
 /INTERCEPT=INCLUDE
 /POSTHOC=C Occupation(TUKEY)
 /PLOT=PROFILE(C*Occupation)
 /EMMEANS=TABLES(C)
 /EMMEANS=TABLES(Occupation)
 /EMMEANS=TABLES(C*Occupation)
 /PRINT=ETASQ HOMOGENEITY DESCRIPTIVE
 /CRITERIA=ALPHA(.05)
 /DESIGN=C Occupation C*Occupation.
```

Levene's Test of Equality of Error Variances[a]

Dependent Variable: Zscore(IT)

F	df1	df2	Sig.
.771	43	4093	.860

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.[a]

a. Design: Intercept + C + Occupation + C * Occupation

Tests of Between-Subjects Effects

Dependent Variable: Zscore(IT)

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	95.424[a]	43	2.219	2.373	.000	.024
Intercept	.581	1	.581	.622	.430	.000
C	6.535	3	2.178	2.329	.072	.002
Occupation	19.615	10	1.962	2.097	.022	.005
C * Occupation	24.770	30	.826	.883	.650	.006
Error	3827.915	4093	.935			
Total	3925.406	4137				
Corrected Total	3923.339	4136				

a. R Squared = .024 (Adjusted R Squared = .014)

```
UNIANOVA ZEC BY C Occupation
 /METHOD=SSTYPE(3)
 /INTERCEPT=INCLUDE
 /POSTHOC=C Occupation(TUKEY)
 /PLOT=PROFILE(C*Occupation)
 /EMMEANS=TABLES(C)
 /EMMEANS=TABLES(Occupation)
 /EMMEANS=TABLES(C*Occupation)
 /PRINT=ETASQ HOMOGENEITY DESCRIPTIVE
 /CRITERIA=ALPHA(.05)
 /DESIGN=C Occupation C*Occupation.
```

Levene's Test of Equality of Error Variances[a]

Dependent Variable: Zscore(EC)

F	df1	df2	Sig.
1.066	43	4093	.357

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.[a]

a. Design: Intercept + C + Occupation + C * Occupation

Tests of Between-Subjects Effects

Dependent Variable: Zscore(EC)

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	102.845[a]	43	2.392	2.542	.000	.026
Intercept	.758	1	.758	.805	.370	.000
C	18.218	3	6.073	6.454	.000	.005
Occupation	20.922	10	2.092	2.224	.014	.005
C * Occupation	24.802	30	.827	.879	.656	.006
Error	3851.082	4093	.941			
Total	3956.226	4137				
Corrected Total	3953.927	4136				

a. R Squared = .026 (Adjusted R Squared = .016)

```
UNIANOVA ZOWD BY C Occupation
 /METHOD=SSTYPE(3)
 /INTERCEPT=INCLUDE
 /POSTHOC=C Occupation(TUKEY)
 /PLOT=PROFILE(C*Occupation)
 /EMMEANS=TABLES(C)
 /EMMEANS=TABLES(Occupation)
 /EMMEANS=TABLES(C*Occupation)
 /PRINT=ETASQ HOMOGENEITY DESCRIPTIVE
 /CRITERIA=ALPHA(.05)
 /DESIGN=C Occupation C*Occupation.
```

Levene's Test of Equality of Error Variances[a]

Dependent Variable: Zscore(OWD)

F	df1	df2	Sig.
.856	43	4093	.735

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.[a]

a. Design: Intercept + C + Occupation + C * Occupation

Tests of Between-Subjects Effects

Dependent Variable: Zscore(OWD)

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	89.702[a]	43	2.086	2.238	.000	.023
Intercept	.032	1	.032	.035	.853	.000
C	7.831	3	2.610	2.801	.039	.002
Occupation	25.437	10	2.544	2.729	.002	.007
C * Occupation	29.141	30	.971	1.042	.403	.008
Error	3814.775	4093	.932			
Total	3906.828	4137				
Corrected Total	3904.477	4136				

a. R Squared = .023 (Adjusted R Squared = .013)

Appendix D

NB. C = Profile, C1 = Organization-based Categorical Profile 1, CPROB1 = Organization-based Continuous Profile 1, OC1 = Occupation-based Categorical Profile 1, OCPROB1 = Occupation-based Continuous Profile 1, PER = Overall Performance, TAD = Thinks and Acts Decisively, LM = Leverages Mastery, IR = Innovates and Reapplies, BDCR = Builds Diverse, Collaborative Relationships, GC = Grows Capability, IT = In Touch, EC = Embraces Change, OWD = Operates with Discipline, Z added before a variable's name refers to a standardized variable in the form of z-score.

One-way ANOVA for PER

```
UNIANOVA PER BY OC
  /METHOD=SSTYPE(3)
  /INTERCEPT=INCLUDE
  /POSTHOC=OC (TUKEY)
  /EMMEANS=TABLES(OC)
  /PRINT=ETASQ HOMOGENEITY DESCRIPTIVE
  /CRITERIA=ALPHA(.05)
  /DESIGN=OC.
```

Levene's Test of Equality of Error Variances[a]

Dependent Variable: PER

F	df1	df2	Sig.
2.321	3	721	.074

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.

a. Design: Intercept + OC

Tests of Between-Subjects Effects

Dependent Variable: PER

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	4.004[a]	3	1.335	1.929	.123	.008
Intercept	6.607	1	6.607	9.550	.002	.013
OC	4.004	3	1.335	1.929	.123	.008

Error	498.862	721	.692
Total	506.268	725	
Corrected Total	502.866	724	

a. R Squared = .008 (Adjusted R Squared = .004)

Multiple Comparisons

Dependent Variable: PER

Tukey HSD

		Mean Difference			95% Confidence Interval	
(I) OC	(J) OC	(I-J)	Std. Error	Sig.	Lower Bound	Upper Bound
1.000	2.000	.0032	.07364	1.000	-.1864	.1928
	3.000	-.0178	.09159	.997	-.2537	.2180
	4.000	.3075	.13820	.117	-.0484	.6634
2.000	1.000	-.0032	.07364	1.000	-.1928	.1864
	3.000	-.0210	.08403	.995	-.2374	.1954
	4.000	.3043	.13331	.103	-.0390	.6476
3.000	1.000	.0178	.09159	.997	-.2180	.2537
	2.000	.0210	.08403	.995	-.1954	.2374
	4.000	.3253	.14401	.109	-.0455	.6961
4.000	1.000	-.3075	.13820	.117	-.6634	.0484
	2.000	-.3043	.13331	.103	-.6476	.0390
	3.000	-.3253	.14401	.109	-.6961	.0455

Based on observed means.

The error term is Mean Square(Error) = .692.

Regression for PER

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT PER
  /METHOD=ENTER ZO ZA ZC ZE ZN.
```

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics R Square Change	F Change	df1	df2	Sig. F Change
1	.180[a]	.032	.026	.82266	.032	4.809	5	719	.000

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-.111	.032		-3.469	.001
	Zscore(O)	-.120	.041	-.141	-2.929	.004
	Zscore(A)	-.017	.040	-.019	-.419	.675
	Zscore(C)	.114	.037	.132	3.103	.002
	Zscore(E)	.111	.040	.128	2.736	.006
	Zscore(N)	-.038	.037	-.045	-1.016	.310

a. Dependent Variable: PER

```
REGRESSION
 /MISSING LISTWISE
 /STATISTICS COEFF OUTS R ANOVA CHANGE
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT PER
 /METHOD=ENTER CPROB1 CPROB2 CPROB3 CPROB4.
```

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics R Square Change	F Change	df1	df2	Sig. F Change
1	.104[a]	.011	.007	.83060	.011	2.632	3	721	.049

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-.003	.057		-.056	.955
	CPROB1	-.038	.110	-.015	-.349	.727

CPROB2	-.420	.164	-.097	-2.566	.010
CPROB4	-.128	.107	-.052	-1.202	.230

a. Dependent Variable: PER

```
REGRESSION
 /MISSING LISTWISE
 /STATISTICS COEFF OUTS R ANOVA CHANGE
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT PER
 /METHOD=ENTER OC1 OC2 OC3.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.089[a]	.008	.004	.83181	.008	1.929	3	721	.123

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	-.359	.125		-2.865	.004
	OClass 1 dummy variable	.307	.138	.166	2.225	.026
	OClass 2 dummy variable	.304	.133	.182	2.283	.023
	OClass 3 dummy variable	.325	.144	.153	2.259	.024

a. Dependent Variable: PER

```
REGRESSION
 /MISSING LISTWISE
 /STATISTICS COEFF OUTS R ANOVA CHANGE
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT PER
 /METHOD=ENTER OCPROB1 OCPROB2 OCPROB3 OCPROB4.
```

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.096[a]	.009	.005	.83129	.009	2.233	3	721	.083

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-.035	.058		-.610	.542
	OCPROB1	-.029	.104	-.012	-.275	.783
	OCPROB3	-.003	.112	-.001	-.028	.978
	OCPROB4	-.367	.146	-.096	-2.509	.012

a. Dependent Variable: PER

Hierarchical regression for PER Dimensions

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT ZTAD
  /METHOD=ENTER ZO ZA ZC ZE ZN
  /METHOD=ENTER OC1 OC2 OC3.
```

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.165[a]	.027	.021	1.01086286	.027	4.041	5	719	.001
2	.177[b]	.031	.021	1.01081380	.004	1.023	3	716	.382

Coefficients[a]

Model	Unstandardized Coefficients	Standardized Coefficients	t	Sig.

		B	Std. Error	Beta		
1	(Constant)	-.176	.039		-4.462	.000
	Zscore(O)	-.117	.050	-.112	-2.323	.020
	Zscore(A)	-.129	.050	-.116	-2.605	.009
	Zscore(C)	.104	.045	.098	2.300	.022
	Zscore(E)	.099	.050	.093	1.991	.047
	Zscore(N)	-.078	.046	-.075	-1.698	.090
2	(Constant)	-.227	.262		-.867	.386
	Zscore(O)	-.089	.066	-.085	-1.357	.175
	Zscore(A)	-.115	.056	-.103	-2.051	.041
	Zscore(C)	.117	.051	.110	2.302	.022
	Zscore(E)	.113	.058	.107	1.945	.052
	Zscore(N)	-.091	.051	-.088	-1.780	.075
	OClass 1 dummy variable	.135	.219	.060	.617	.537
	OClass 2 dummy variable	.058	.302	.028	.193	.847
	OClass 3 dummy variable	-.123	.420	-.047	-.292	.770

a. Dependent Variable: Zscore(TAD)

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT ZTAD
  /METHOD=ENTER ZO ZA ZC ZE ZN
  /METHOD=ENTER OCPROB1 OCPROB2 OCPROB3 OCPROB4.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.165[a]	.027	.021	1.01086286	.027	4.041	5	719	.001

2	.184[b]	.034	.023	1.00958670	.007	1.606	3	716	.187

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT ZLM
  /METHOD=ENTER ZO ZA ZC ZE ZN
  /METHOD=ENTER OC1 OC2 OC3.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.130[a]	.017	.010	.98544857	.017	2.483	5	719	.030
2	.173[b]	.030	.019	.98092636	.013	3.215	3	716	.022

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-.091	.038		-2.356	.019
	Zscore(O)	-.100	.049	-.099	-2.043	.041
	Zscore(A)	-.054	.048	-.050	-1.115	.265
	Zscore(C)	.070	.044	.068	1.586	.113
	Zscore(E)	.142	.048	.138	2.934	.003
	Zscore(N)	.033	.045	.033	.733	.464
2	(Constant)	.090	.254		.354	.723
	Zscore(O)	-.010	.064	-.010	-.161	.872
	Zscore(A)	-.008	.054	-.007	-.141	.888
	Zscore(C)	.114	.049	.111	2.324	.020
	Zscore(E)	.194	.056	.189	3.448	.001
	Zscore(N)	-.012	.049	-.012	-.236	.813
	OClass 1 dummy variable	.050	.212	.023	.238	.812
	OClass 2 dummy variable	-.236	.293	-.119	-.804	.421

OClass 3 dummy variable	-.609	.407	-.241	-1.495	.135

a. Dependent Variable: Zscore(LM)

```
REGRESSION
 /MISSING LISTWISE
 /STATISTICS COEFF OUTS R ANOVA CHANGE
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT ZLM
 /METHOD=ENTER ZO ZA ZC ZE ZN
 /METHOD=ENTER OCPROB1 OCPROB2 OCPROB3 OCPROB4.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.130[a]	.017	.010	.98544857	.017	2.483	5	719	.030
2	.188[b]	.035	.025	.97824444	.018	4.543	3	716	.004

```
REGRESSION
 /MISSING LISTWISE
 /STATISTICS COEFF OUTS R ANOVA CHANGE
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT ZIR
 /METHOD=ENTER ZO ZA ZC ZE ZN
 /METHOD=ENTER OC1 OC2 OC3.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	
1	.155[a]	.024	.017	1.00499459	.024	3.535	5	719	Sig. F Change
2	.165[b]	.027	.016	1.00539698	.003	.808	3	716	.004
									.490

Coefficients[a]

Model	Unstandardized Coefficients	Standardized Coefficients	t	Sig.

Model		B	Std. Error	Beta	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-.178	.039		-4.548	.000
	Zscore(O)	-.039	.050	-.037	-.773	.440
	Zscore(A)	-.051	.049	-.046	-1.040	.299
	Zscore(C)	.071	.045	.067	1.576	.115
	Zscore(E)	.139	.049	.132	2.817	.005
	Zscore(N)	-.044	.046	-.042	-.958	.338
2	(Constant)	-.083	.260		-.320	.749
	Zscore(O)	.010	.065	.010	.152	.880
	Zscore(A)	-.034	.056	-.031	-.611	.541
	Zscore(C)	.091	.050	.087	1.812	.070
	Zscore(E)	.162	.058	.154	2.797	.005
	Zscore(N)	-.066	.051	-.064	-1.302	.193
	OClass 1 dummy variable	.044	.218	.020	.204	.838
	OClass 2 dummy variable	-.156	.300	-.077	-.519	.604
	OClass 3 dummy variable	-.256	.417	-.099	-.612	.540

a. Dependent Variable: Zscore(IR)

```
REGRESSION
 /MISSING LISTWISE
 /STATISTICS COEFF OUTS R ANOVA CHANGE
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT ZIR
 /METHOD=ENTER ZO ZA ZC ZE ZN
 /METHOD=ENTER OCPROB1 OCPROB2 OCPROB3 OCPROB4.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.155[a]	.024	.017	1.00499459	.024	3.535	5	719	.004
2	.167[b]	.028	.017	1.00516990	.004	.916	3	716	.432

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT ZLeads
  /METHOD=ENTER ZO ZA ZC ZE ZN
  /METHOD=ENTER OC1 OC2 OC3.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.187[a]	.035	.028	.99279495	.035	5.197	5	719	.000
2	.203[b]	.041	.030	.99167842	.006	1.540	3	716	.203

Coefficients[a]

		Unstandardized Coefficients		Standardized Coefficients		
Model		B	Std. Error	Beta	t	Sig.
1	(Constant)	-.068	.039		-1.758	.079
	Zscore(O)	-.148	.049	-.144	-2.986	.003
	Zscore(A)	.016	.049	.014	.326	.745
	Zscore(C)	.109	.044	.104	2.467	.014
	Zscore(E)	.131	.049	.125	2.684	.007
	Zscore(N)	-.075	.045	-.073	-1.667	.096
2	(Constant)	.088	.257		.343	.731
	Zscore(O)	-.078	.064	-.076	-1.218	.224
	Zscore(A)	.048	.055	.044	.879	.379
	Zscore(C)	.142	.050	.136	2.862	.004
	Zscore(E)	.169	.057	.162	2.970	.003
	Zscore(N)	-.109	.050	-.106	-2.174	.030
	OClass 1 dummy variable	.025	.215	.011	.118	.906
	OClass 2 dummy variable	-.215	.296	-.107	-.727	.467

OClass 3 dummy variable	-.451	.412	-.176	-1.095	.274

a. Dependent Variable: Zscore(Leads)

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT ZLeads
  /METHOD=ENTER ZO ZA ZC ZE ZN
  /METHOD=ENTER OCPROB1 OCPROB2 OCPROB3 OCPROB4.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.187[a]	.035	.028	.99279495	.035	5.197	5	719	.000
2	.203[b]	.041	.030	.99168729	.006	1.536	3	716	.204

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT ZBDCR
  /METHOD=ENTER ZO ZA ZC ZE ZN
  /METHOD=ENTER OC1 OC2 OC3.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.232[a]	.054	.047	.97763755	.054	8.190	5	719	.000
2	.236[b]	.056	.045	.97872161	.002	.469	3	716	.704

Coefficients[a]

Model	Unstandardized Coefficients	Standardized Coefficients	t	Sig.

		B	Std. Error	Beta		
1	(Constant)	-.132	.038		-3.461	.001
	Zscore(O)	-.261	.049	-.255	-5.361	.000
	Zscore(A)	.169	.048	.154	3.510	.000
	Zscore(C)	.101	.044	.097	2.308	.021
	Zscore(E)	.125	.048	.121	2.611	.009
	Zscore(N)	-.005	.044	-.005	-.114	.909
2	(Constant)	-.018	.253		-.072	.942
	Zscore(O)	-.220	.064	-.215	-3.468	.001
	Zscore(A)	.188	.054	.172	3.460	.001
	Zscore(C)	.120	.049	.116	2.452	.014
	Zscore(E)	.149	.056	.143	2.643	.008
	Zscore(N)	-.025	.049	-.025	-.510	.611
	OClass 1 dummy variable	-.009	.212	-.004	-.045	.965
	OClass 2 dummy variable	-.152	.292	-.076	-.521	.602
	OClass 3 dummy variable	-.281	.406	-.110	-.693	.489

a. Dependent Variable: Zscore(BDCR)

```
REGRESSION
 /MISSING LISTWISE
 /STATISTICS COEFF OUTS R ANOVA CHANGE
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT ZBDCR
 /METHOD=ENTER ZO ZA ZC ZE ZN
 /METHOD=ENTER OCPROB1 OCPROB2 OCPROB3 OCPROB4.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.232[a]	.054	.047	.97763755	.054	8.190	5	719	.000
2	.238[b]	.056	.046	.97835989	.003	.646	3	716	.585

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT ZGC
  /METHOD=ENTER ZO ZA ZC ZE ZN
  /METHOD=ENTER OC1 OC2 OC3.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.137[a]	.019	.012	1.00508243	.019	2.762	5	719	.018
2	.153[b]	.023	.012	1.00484613	.005	1.113	3	716	.343

Coefficients[a]

		Unstandardized Coefficients		Standardized Coefficients		
Model		B	Std. Error	Beta	t	Sig.
1	(Constant)	-.149	.039		-3.799	.000
	Zscore(O)	-.087	.050	-.084	-1.736	.083
	Zscore(A)	-.004	.049	-.004	-.089	.929
	Zscore(C)	.123	.045	.117	2.744	.006
	Zscore(E)	.089	.049	.084	1.797	.073
	Zscore(N)	-.018	.046	-.017	-.391	.696
2	(Constant)	.060	.260		.231	.818
	Zscore(O)	-.033	.065	-.032	-.504	.614
	Zscore(A)	.033	.056	.030	.587	.558
	Zscore(C)	.154	.050	.147	3.064	.002
	Zscore(E)	.129	.058	.123	2.231	.026
	Zscore(N)	-.047	.051	-.046	-.930	.353
	OClass 1 dummy variable	-.099	.217	-.044	-.455	.649
	OClass 2 dummy variable	-.227	.300	-.112	-.758	.449

OClass 3 dummy variable	-.512	.417	-.199	-1.228	.220

a. Dependent Variable: Zscore(GC)

```
REGRESSION
 /MISSING LISTWISE
 /STATISTICS COEFF OUTS R ANOVA CHANGE
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT ZGC
 /METHOD=ENTER ZO ZA ZC ZE ZN
 /METHOD=ENTER OCPROB1 OCPROB2 OCPROB3 OCPROB4.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.137[a]	.019	.012	1.00508243	.019	2.762	5	719	.018
2	.164[b]	.027	.016	1.00309469	.008	1.951	3	716	.120

```
REGRESSION
 /MISSING LISTWISE
 /STATISTICS COEFF OUTS R ANOVA CHANGE
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT ZIT
 /METHOD=ENTER ZO ZA ZC ZE ZN
 /METHOD=ENTER OC1 OC2 OC3.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.143[a]	.020	.014	.98821887	.020	2.999	5	719	.011
2	.155[b]	.024	.013	.98846369	.004	.881	3	716	.450

Coefficients[a]

	Unstandardized Coefficients		Standardized Coefficients		
Model	B	Std. Error	Beta	t	Sig.

1	(Constant)	.038	.039		.985	.325
	Zscore(O)	-.135	.049	-.133	-2.738	.006
	Zscore(A)	-.021	.049	-.020	-.437	.662
	Zscore(C)	.112	.044	.109	2.547	.011
	Zscore(E)	.077	.049	.075	1.593	.112
	Zscore(N)	-.055	.045	-.055	-1.237	.216
2	(Constant)	.234	.256		.914	.361
	Zscore(O)	-.081	.064	-.080	-1.262	.207
	Zscore(A)	.012	.055	.011	.217	.828
	Zscore(C)	.142	.050	.137	2.860	.004
	Zscore(E)	.114	.057	.111	2.012	.045
	Zscore(N)	-.084	.050	-.083	-1.680	.093
	OClass 1 dummy variable	-.078	.214	-.035	-.363	.716
	OClass 2 dummy variable	-.227	.295	-.114	-.771	.441
	OClass 3 dummy variable	-.468	.410	-.185	-1.140	.255

a. Dependent Variable: Zscore(IT)

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT ZIT
  /METHOD=ENTER ZO ZA ZC ZE ZN
  /METHOD=ENTER OCPROB1 OCPROB2 OCPROB3 OCPROB4.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.143[a]	.020	.014	.98821887	.020	2.999	5	719	.011
2	.161[b]	.026	.015	.98754165	.005	1.329	3	716	.264

REGRESSION

```
/MISSING LISTWISE
/STATISTICS COEFF OUTS R ANOVA CHANGE
/CRITERIA=PIN(.05) POUT(.10)
/NOORIGIN
/DEPENDENT ZEC
/METHOD=ENTER ZO ZA ZC ZE ZN
/METHOD=ENTER OC1 OC2 OC3.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.149[a]	.022	.015	.98448803	.022	3.259	5	719	.006
2	.157[b]	.025	.014	.98525158	.003	.629	3	716	.597

Coefficients[a]

		Unstandardized Coefficients		Standardized Coefficients		
Model		B	Std. Error	Beta	t	Sig.
1	(Constant)	-.103	.038		-2.673	.008
	Zscore(O)	-.047	.049	-.046	-.955	.340
	Zscore(A)	.029	.048	.027	.601	.548
	Zscore(C)	.097	.044	.094	2.215	.027
	Zscore(E)	.088	.048	.085	1.810	.071
	Zscore(N)	-.026	.045	-.026	-.593	.553
2	(Constant)	-.155	.255		-.609	.543
	Zscore(O)	-.024	.064	-.024	-.374	.708
	Zscore(A)	.038	.055	.035	.688	.492
	Zscore(C)	.107	.049	.103	2.156	.031
	Zscore(E)	.097	.057	.094	1.707	.088
	Zscore(N)	-.036	.050	-.036	-.732	.464
	OClass 1 dummy variable	.128	.213	.058	.602	.547
	OClass 2 dummy variable	.049	.294	.025	.166	.868
	OClass 3 dummy variable	-.066	.409	-.026	-.160	.873

a. Dependent Variable: Zscore(EC)

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT ZEC
  /METHOD=ENTER ZO ZA ZC ZE ZN
  /METHOD=ENTER OCPROB1 OCPROB2 OCPROB3 OCPROB4.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.149[a]	.022	.015	.98448803	.022	3.259	5	719	.006
2	.163[b]	.027	.016	.98435427	.004	1.065	3	716	.363

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT ZOWD
  /METHOD=ENTER ZO ZA ZC ZE ZN
  /METHOD=ENTER OC1 OC2 OC3.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.242[a]	.059	.052	.96828641	.059	8.945	5	719	.000
2	.249[b]	.062	.051	.96863994	.003	.825	3	716	.480

Coefficients[a]

		Unstandardized Coefficients		Standardized Coefficients		
Model		B	Std. Error	Beta	t	Sig.
1	(Constant)	-.143	.038		-3.797	.000
	Zscore(O)	-.147	.048	-.145	-3.050	.002
	Zscore(A)	-.106	.048	-.097	-2.221	.027
	Zscore(C)	.238	.043	.231	5.515	.000

	Zscore(E)	.105	.048	.102	2.209	.028
	Zscore(N)	-.072	.044	-.072	-1.653	.099
2	(Constant)	-.145	.251		-.577	.564
	Zscore(O)	-.110	.063	-.109	-1.753	.080
	Zscore(A)	-.094	.054	-.087	-1.749	.081
	Zscore(C)	.253	.049	.245	5.200	.000
	Zscore(E)	.120	.056	.116	2.150	.032
	Zscore(N)	-.089	.049	-.088	-1.815	.070
	OClass 1 dummy variable	.118	.210	.053	.563	.574
	OClass 2 dummy variable	-.034	.289	-.017	-.118	.906
	OClass 3 dummy variable	-.136	.402	-.054	-.337	.736

a. Dependent Variable: Zscore(OWD)

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT ZOWD
  /METHOD=ENTER ZO ZA ZC ZE ZN
  /METHOD=ENTER OCPROB1 OCPROB2 OCPROB3 OCPROB4.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.242[a]	.059	.052	.96828641	.059	8.945	5	719	.000
2	.247[b]	.061	.051	.96904454	.002	.625	3	716	.599

Appendix E

NB. C = Profile, C1 = Organization-based Categorical Profile 1, CPROB1 = Organization-based Continuous Profile 1, OC1 = Occupation-based Categorical Profile 1, OCPROB1 = Occupation-based Continuous Profile 1, PER = Overall Performance, TAD = Thinks and Acts Decisively, LM = Leverages Mastery, IR = Innovates and Reapplies, BDCR = Builds Diverse, Collaborative Relationships, GC = Grows Capability, IT = In Touch, EC = Embraces Change, OWD = Operates with Discipline, Z added before a variable's name refers to a standardized variable in the form of z-score.

<u>One-way ANOVA for PER</u>

```
UNIANOVA PER BY OC
  /METHOD=SSTYPE(3)
  /INTERCEPT=INCLUDE
  /POSTHOC=OC (TUKEY)
  /EMMEANS=TABLES(OC)
  /PRINT=ETASQ HOMOGENEITY DESCRIPTIVE
  /CRITERIA=ALPHA(.05)
  /DESIGN=OC.
```

Levene's Test of Equality of Error Variances[a]

Dependent Variable: PER

F	df1	df2	Sig.
.648	3	421	.584

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.

a. Design: Intercept + OC

Tests of Between-Subjects Effects

Dependent Variable: PER

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	8.955[a]	3	2.985	5.245	.001	.036
Intercept	.618	1	.618	1.086	.298	.003
OC	8.955	3	2.985	5.245	.001	.036

Error	239.602	421	.569
Total	249.081	425	
Corrected Total	248.557	424	

a. R Squared = .036 (Adjusted R Squared = .029)

Multiple Comparisons

Dependent Variable: PER

Tukey HSD

		Mean Difference			95% Confidence Interval	
(I) OC	(J) OC	(I-J)	Std. Error	Sig.	Lower Bound	Upper Bound
1.000	2.000	-.6842*	.17527	.001	-1.1362	-.2321
	3.000	-.3168	.12454	.055	-.6381	.0044
	4.000	-.3609*	.13184	.033	-.7010	-.0209
2.000	1.000	.6842*	.17527	.001	.2321	1.1362
	3.000	.3673	.14269	.051	-.0007	.7354
	4.000	.3232	.14910	.134	-.0613	.7078
3.000	1.000	.3168	.12454	.055	-.0044	.6381
	2.000	-.3673	.14269	.051	-.7354	.0007
	4.000	-.0441	.08379	.953	-.2602	.1721
4.000	1.000	.3609*	.13184	.033	.0209	.7010
	2.000	-.3232	.14910	.134	-.7078	.0613
	3.000	.0441	.08379	.953	-.1721	.2602

Based on observed means.

The error term is Mean Square(Error) = .569.

*. The mean difference is significant at the .05 level.

Regression for PER

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT PER
  /METHOD=ENTER ZO ZA ZC ZE ZN.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.197[a]	.039	.027	.75509	.039	3.388	5	419	.005

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.052	.037		1.388	.166
	Zscore(O)	-.026	.050	-.032	-.512	.609
	Zscore(A)	-.074	.047	-.092	-1.587	.113
	Zscore(C)	.019	.043	.023	.431	.666
	Zscore(E)	.149	.048	.195	3.133	.002
	Zscore(N)	-.045	.045	-.057	-.999	.318

a. Dependent Variable: PER

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT PER
  /METHOD=ENTER CPROB1 CPROB2 CPROB3 CPROB4.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.151[a]	.023	.016	.75957	.023	3.273	3	421	.021

Coefficients[a]

Model	Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.

1	(Constant)	.108	.070		1.532	.126
	CPROB1	-.034	.149	-.013	-.228	.819
	CPROB2	-.527	.173	-.152	-3.049	.002
	CPROB4	-.094	.123	-.043	-.767	.444

a. Dependent Variable: PER

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT PER
  /METHOD=ENTER OC1 OC2 OC3.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.190[a]	.036	.029	.75440	.036	5.245	3	421	.001

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.071	.067		1.065	.287
	OClass 1 dummy variable	-.361	.132	-.144	-2.738	.006
	OClass 2 dummy variable	.323	.149	.112	2.168	.031
	OClass 3 dummy variable	-.044	.084	-.029	-.526	.599

a. Dependent Variable: PER

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
```

```
/DEPENDENT PER
/METHOD=ENTER OCPROB1 OCPROB2 OCPROB3 OCPROB4.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.181[a]	.033	.026	.75564	.033	4.770	3	421	.003

Coefficients[a]

		Unstandardized Coefficients		Standardized Coefficients		
Model		B	Std. Error	Beta	t	Sig.
1	(Constant)	-.004	.059		-.075	.941
	OCPROB1	-.303	.140	-.110	-2.167	.031
	OCPROB2	.442	.177	.126	2.489	.013
	OCPROB4	.101	.101	.053	.995	.321

a. Dependent Variable: PER

Hierarchical regression for PER Dimensions

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT ZTAD
  /METHOD=ENTER ZO ZA ZC ZE ZN
  /METHOD=ENTER OC1 OC2 OC3.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.215[a]	.046	.035	.92930372	.046	4.055	5	419	.001
2	.263[b]	.069	.051	.92129878	.023	3.438	3	416	.017

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.099	.046		2.147	.032
	Zscore(O)	-.024	.062	-.025	-.396	.692
	Zscore(A)	-.146	.058	-.147	-2.534	.012
	Zscore(C)	.042	.053	.043	.794	.427
	Zscore(E)	.205	.059	.218	3.511	.000
	Zscore(N)	-.029	.055	-.030	-.519	.604
2	(Constant)	-.089	.136		-.652	.515
	Zscore(O)	-.025	.070	-.025	-.362	.718
	Zscore(A)	-.073	.073	-.074	-1.003	.316
	Zscore(C)	.066	.056	.067	1.191	.234
	Zscore(E)	.210	.063	.222	3.345	.001
	Zscore(N)	-.029	.063	-.030	-.459	.646
	OClass 1 dummy variable	.079	.338	.025	.233	.816
	OClass 2 dummy variable	.610	.270	.170	2.255	.025
	OClass 3 dummy variable	.254	.166	.134	1.527	.127

a. Dependent Variable: Zscore(TAD)

```
REGRESSION
 /MISSING LISTWISE
 /STATISTICS COEFF OUTS R ANOVA CHANGE
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT ZTAD
 /METHOD=ENTER ZO ZA ZC ZE ZN
 /METHOD=ENTER OCPROB1 OCPROB2 OCPROB3 OCPROB4.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change

1	.215[a]	.046	.035	.92930372	.046	4.055	5	419	.001
2	.254[b]	.065	.047	.92359493	.018	2.732	3	416	.043

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT ZLM
  /METHOD=ENTER ZO ZA ZC ZE ZN
  /METHOD=ENTER OC1 OC2 OC3.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.161[a]	.026	.014	.96606912	.026	2.230	5	419	.050
2	.173[b]	.030	.011	.96750866	.004	.585	3	416	.625

Coefficients[a]

		Unstandardized Coefficients		Standardized Coefficients		
Model		B	Std. Error	Beta	t	Sig.
1	(Constant)	.112	.048		2.329	.020
	Zscore(O)	-.024	.064	-.023	-.373	.710
	Zscore(A)	-.140	.060	-.137	-2.327	.020
	Zscore(C)	.072	.056	.071	1.299	.195
	Zscore(E)	.144	.061	.148	2.365	.019
	Zscore(N)	-.008	.057	-.008	-.134	.894
2	(Constant)	.087	.143		.614	.540
	Zscore(O)	-.041	.073	-.040	-.564	.573
	Zscore(A)	-.111	.076	-.108	-1.447	.149
	Zscore(C)	.081	.058	.080	1.388	.166
	Zscore(E)	.134	.066	.138	2.037	.042
	Zscore(N)	.007	.066	.007	.107	.915
	OClass 1 dummy variable	-.097	.355	-.030	-.272	.785

OClass 2 dummy variable	.229	.284	.062	.806	.420
OClass 3 dummy variable	.028	.175	.015	.163	.871

a. Dependent Variable: Zscore(LM)

```
REGRESSION
 /MISSING LISTWISE
 /STATISTICS COEFF OUTS R ANOVA CHANGE
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT ZLM
 /METHOD=ENTER ZO ZA ZC ZE ZN
 /METHOD=ENTER OCPROB1 OCPROB2 OCPROB3 OCPROB4.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.161[a]	.026	.014	.96606912	.026	2.230	5	419	.050
2	.178[b]	.032	.013	.96659842	.006	.847	3	416	.469

```
REGRESSION
 /MISSING LISTWISE
 /STATISTICS COEFF OUTS R ANOVA CHANGE
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT ZIR
 /METHOD=ENTER ZO ZA ZC ZE ZN
 /METHOD=ENTER OC1 OC2 OC3.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.219[a]	.048	.037	.95630650	.048	4.214	5	419	.001
2	.250[b]	.062	.044	.95243433	.014	2.138	3	416	.095

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-.110	.047		-2.325	.021
	Zscore(O)	.020	.063	.019	.314	.753
	Zscore(A)	-.088	.059	-.086	-1.479	.140
	Zscore(C)	-.086	.055	-.084	-1.556	.121
	Zscore(E)	.176	.060	.181	2.926	.004
	Zscore(N)	-.081	.057	-.082	-1.428	.154
2	(Constant)	-.259	.140		-1.848	.065
	Zscore(O)	.015	.072	.015	.211	.833
	Zscore(A)	-.018	.075	-.018	-.244	.807
	Zscore(C)	-.063	.057	-.061	-1.090	.276
	Zscore(E)	.178	.065	.183	2.747	.006
	Zscore(N)	-.079	.065	-.080	-1.221	.223
	OClass 1 dummy variable	.081	.350	.025	.231	.817
	OClass 2 dummy variable	.539	.280	.146	1.927	.055
	OClass 3 dummy variable	.190	.172	.097	1.103	.271

a. Dependent Variable: Zscore(IR)

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT ZIR
  /METHOD=ENTER ZO ZA ZC ZE ZN
  /METHOD=ENTER OCPROB1 OCPROB2 OCPROB3 OCPROB4.
```

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change
1	.219[a]	.048	.037	.95630650	.048	4.214	5	419	.001

2	.239[b]	.057	.039	.95518508	.009	1.328	3	416	.265

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT ZLeads
  /METHOD=ENTER ZO ZA ZC ZE ZN
  /METHOD=ENTER OC1 OC2 OC3.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.226[a]	.051	.040	.88517003	.051	4.511	5	419	.001
2	.249[b]	.062	.044	.88329910	.011	1.592	3	416	.191

Coefficients[a]

		Unstandardized Coefficients		Standardized Coefficients		
Model		B	Std. Error	Beta	t	Sig.
1	(Constant)	.042	.044		.962	.337
	Zscore(O)	-.016	.059	-.017	-.271	.786
	Zscore(A)	-.045	.055	-.048	-.828	.408
	Zscore(C)	-.047	.051	-.049	-.914	.361
	Zscore(E)	.214	.056	.237	3.835	.000
	Zscore(N)	-.031	.052	-.034	-.599	.549
2	(Constant)	-.125	.130		-.964	.336
	Zscore(O)	-.004	.067	-.005	-.067	.947
	Zscore(A)	.015	.070	.016	.221	.825
	Zscore(C)	-.026	.053	-.027	-.480	.631
	Zscore(E)	.226	.060	.251	3.757	.000
	Zscore(N)	-.044	.060	-.048	-.732	.465
	OClass 1 dummy variable	.203	.324	.069	.626	.531
	OClass 2 dummy variable	.466	.259	.136	1.797	.073

OClass 3 dummy variable	.215	.159	.119	1.346	.179

a. Dependent Variable: Zscore(Leads)

```
REGRESSION
 /MISSING LISTWISE
 /STATISTICS COEFF OUTS R ANOVA CHANGE
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT ZLeads
 /METHOD=ENTER ZO ZA ZC ZE ZN
 /METHOD=ENTER OCPROB1 OCPROB2 OCPROB3 OCPROB4.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.226[a]	.051	.040	.88517003	.051	4.511	5	419	.001
2	.248[b]	.062	.044	.88343852	.010	1.548	3	416	.202

```
REGRESSION
 /MISSING LISTWISE
 /STATISTICS COEFF OUTS R ANOVA CHANGE
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT ZBDCR
 /METHOD=ENTER ZO ZA ZC ZE ZN
 /METHOD=ENTER OC1 OC2 OC3.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.191[a]	.037	.025	.91906448	.037	3.177	5	419	.008
2	.208[b]	.043	.025	.91919648	.007	.960	3	416	.412

Coefficients[a]

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		

1	(Constant)	.032	.046		.702	.483
	Zscore(O)	-.100	.061	-.102	-1.643	.101
	Zscore(A)	.193	.057	.197	3.379	.001
	Zscore(C)	-.062	.053	-.064	-1.174	.241
	Zscore(E)	.066	.058	.071	1.140	.255
	Zscore(N)	-.015	.054	-.016	-.273	.785
2	(Constant)	.040	.135		.295	.768
	Zscore(O)	-.131	.070	-.134	-1.885	.060
	Zscore(A)	.226	.073	.232	3.116	.002
	Zscore(C)	-.052	.055	-.053	-.939	.348
	Zscore(E)	.047	.063	.051	.759	.448
	Zscore(N)	.011	.063	.012	.179	.858
	OClass 1 dummy variable	-.185	.337	-.061	-.549	.583
	OClass 2 dummy variable	.249	.270	.071	.923	.356
	OClass 3 dummy variable	-.021	.166	-.011	-.128	.898

a. Dependent Variable: Zscore(BDCR)

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT ZBDCR
  /METHOD=ENTER ZO ZA ZC ZE ZN
  /METHOD=ENTER OCPROB1 OCPROB2 OCPROB3 OCPROB4.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.191[a]	.037	.025	.91906448	.037	3.177	5	419	.008
2	.202[b]	.041	.023	.92023009	.004	.646	3	416	.586

REGRESSION

```
/MISSING LISTWISE
/STATISTICS COEFF OUTS R ANOVA CHANGE
/CRITERIA=PIN(.05) POUT(.10)
/NOORIGIN
/DEPENDENT ZGC
/METHOD=ENTER ZO ZA ZC ZE ZN
/METHOD=ENTER OC1 OC2 OC3.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.177[a]	.031	.020	.94462839	.031	2.722	5	419	.020
2	.230[b]	.053	.035	.93745923	.021	3.144	3	416	.025

Coefficients[a]

		Unstandardized Coefficients		Standardized Coefficients		
Model		B	Std. Error	Beta	t	Sig.
1	(Constant)	.104	.047		2.216	.027
	Zscore(O)	.083	.063	.083	1.334	.183
	Zscore(A)	-.147	.059	-.147	-2.509	.012
	Zscore(C)	.066	.054	.066	1.214	.226
	Zscore(E)	.077	.059	.081	1.297	.195
	Zscore(N)	-.049	.056	-.051	-.881	.379
2	(Constant)	-.113	.138		-.815	.416
	Zscore(O)	.085	.071	.085	1.195	.233
	Zscore(A)	-.032	.074	-.032	-.439	.661
	Zscore(C)	.106	.057	.106	1.873	.062
	Zscore(E)	.087	.064	.092	1.368	.172
	Zscore(N)	-.059	.064	-.061	-.922	.357
	OClass 1 dummy variable	.310	.344	.099	.900	.368
	OClass 2 dummy variable	.777	.275	.215	2.825	.005
	OClass 3 dummy variable	.238	.169	.125	1.409	.159

a. Dependent Variable: Zscore(GC)

```
REGRESSION
 /MISSING LISTWISE
 /STATISTICS COEFF OUTS R ANOVA CHANGE
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT ZGC
 /METHOD=ENTER ZO ZA ZC ZE ZN
 /METHOD=ENTER OCPROB1 OCPROB2 OCPROB3 OCPROB4.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.177[a]	.031	.020	.94462839	.031	2.722	5	419	.020
2	.218[b]	.048	.029	.94012942	.016	2.340	3	416	.073

```
REGRESSION
 /MISSING LISTWISE
 /STATISTICS COEFF OUTS R ANOVA CHANGE
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT ZIT
 /METHOD=ENTER ZO ZA ZC ZE ZN
 /METHOD=ENTER OC1 OC2 OC3.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.135[a]	.018	.007	.98274287	.018	1.567	5	419	.168
2	.172[b]	.030	.011	.98059686	.011	1.612	3	416	.186

Coefficients[a]

		Unstandardized Coefficients		Standardized Coefficients		
Model		B	Std. Error	Beta	t	Sig.
1	(Constant)	-.020	.049		-.402	.688
	Zscore(O)	-.040	.065	-.038	-.608	.543

	Zscore(A)	-.016	.061	-.016	-.265	.791
	Zscore(C)	-.029	.057	-.028	-.509	.611
	Zscore(E)	.124	.062	.126	2.005	.046
	Zscore(N)	-.059	.058	-.059	-1.020	.309
2	(Constant)	.027	.144		.184	.854
	Zscore(O)	-.090	.074	-.087	-1.211	.227
	Zscore(A)	.021	.077	.020	.265	.791
	Zscore(C)	-.019	.059	-.018	-.316	.752
	Zscore(E)	.093	.067	.094	1.391	.165
	Zscore(N)	-.016	.067	-.016	-.240	.811
	OClass 1 dummy variable	-.342	.360	-.106	-.951	.342
	OClass 2 dummy variable	.282	.288	.075	.978	.329
	OClass 3 dummy variable	-.072	.177	-.036	-.405	.685

a. Dependent Variable: Zscore(IT)

```
REGRESSION
 /MISSING LISTWISE
 /STATISTICS COEFF OUTS R ANOVA CHANGE
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT ZIT
 /METHOD=ENTER ZO ZA ZC ZE ZN
 /METHOD=ENTER OCPROB1 OCPROB2 OCPROB3 OCPROB4.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.135[a]	.018	.007	.98274287	.018	1.567	5	419	.168
2	.155[b]	.024	.005	.98345657	.006	.797	3	416	.496

```
REGRESSION
 /MISSING LISTWISE
 /STATISTICS COEFF OUTS R ANOVA CHANGE
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
```

```
/DEPENDENT ZEC
/METHOD=ENTER ZO ZA ZC ZE ZN
/METHOD=ENTER OC1 OC2 OC3.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.198[a]	.039	.028	.93392875	.039	3.422	5	419	.005
2	.230[b]	.053	.035	.93049781	.014	2.032	3	416	.109

Coefficients[a]

		Unstandardized Coefficients		Standardized Coefficients		
Model		B	Std. Error	Beta	t	Sig.
1	(Constant)	.111	.046		2.386	.017
	Zscore(O)	-.097	.062	-.098	-1.571	.117
	Zscore(A)	-.062	.058	-.062	-1.071	.285
	Zscore(C)	.018	.054	.018	.337	.736
	Zscore(E)	.189	.059	.200	3.222	.001
	Zscore(N)	-.077	.055	-.079	-1.383	.168
2	(Constant)	.074	.137		.538	.591
	Zscore(O)	-.122	.071	-.123	-1.733	.084
	Zscore(A)	-.039	.074	-.039	-.528	.598
	Zscore(C)	.023	.056	.023	.414	.679
	Zscore(E)	.173	.063	.184	2.739	.006
	Zscore(N)	-.051	.063	-.053	-.810	.418
	OClass 1 dummy variable	-.254	.342	-.082	-.744	.457
	OClass 2 dummy variable	.280	.273	.078	1.025	.306
	OClass 3 dummy variable	.075	.168	.040	.449	.653

a. Dependent Variable: Zscore(EC)

```
REGRESSION
 /MISSING LISTWISE
 /STATISTICS COEFF OUTS R ANOVA CHANGE
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT ZEC
 /METHOD=ENTER ZO ZA ZC ZE ZN
 /METHOD=ENTER OCPROB1 OCPROB2 OCPROB3 OCPROB4.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.198[a]	.039	.028	.93392875	.039	3.422	5	419	.005
2	.228[b]	.052	.034	.93114687	.013	1.836	3	416	.140

```
REGRESSION
 /MISSING LISTWISE
 /STATISTICS COEFF OUTS R ANOVA CHANGE
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT ZOWD
 /METHOD=ENTER ZO ZA ZC ZE ZN
 /METHOD=ENTER OC1 OC2 OC3.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.254[a]	.064	.053	.93401764	.064	5.767	5	419	.000
2	.283[b]	.080	.063	.92936364	.016	2.402	3	416	.067

Coefficients[a]

		Unstandardized Coefficients		Standardized Coefficients		
Model		B	Std. Error	Beta	t	Sig.
1	(Constant)	.098	.046		2.126	.034
	Zscore(O)	-.033	.062	-.033	-.529	.597
	Zscore(A)	-.218	.058	-.216	-3.756	.000
	Zscore(C)	.193	.054	.192	3.588	.000

	Zscore(E)	.145	.059	.151	2.465	.014
	Zscore(N)	-.054	.055	-.055	-.971	.332
2	(Constant)	.034	.137		.246	.806
	Zscore(O)	-.065	.070	-.065	-.927	.354
	Zscore(A)	-.142	.073	-.141	-1.939	.053
	Zscore(C)	.217	.056	.216	3.876	.000
	Zscore(E)	.129	.063	.135	2.039	.042
	Zscore(N)	-.030	.063	-.030	-.467	.641
	OClass 1 dummy variable	-.085	.341	-.027	-.248	.804
	OClass 2 dummy variable	.530	.273	.146	1.941	.053
	OClass 3 dummy variable	.056	.168	.029	.337	.736

a. Dependent Variable: Zscore(OWD)

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT ZOWD
  /METHOD=ENTER ZO ZA ZC ZE ZN
  /METHOD=ENTER OCPROB1 OCPROB2 OCPROB3 OCPROB4.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.254[a]	.064	.053	.93401764	.064	5.767	5	419	.000
2	.272[b]	.074	.056	.93250974	.010	1.452	3	416	.227

Appendix F

NB. C = Profile, C1 = Organization-based Categorical Profile 1, CPROB1 = Organization-based Continuous Profile 1, OC1 = Occupation-based Categorical Profile 1, OCPROB1 = Occupation-based Continuous Profile 1, PER = Overall Performance, TAD = Thinks and Acts Decisively, LM = Leverages Mastery, IR = Innovates and Reapplies, BDCR = Builds Diverse, Collaborative Relationships, GC = Grows Capability, IT = In Touch, EC = Embraces Change, OWD = Operates with Discipline, Z added before a variable's name refers to a standardized variable in the form of z-score.

One-way ANOVA for PER

```
UNIANOVA PER BY OC
  /METHOD=SSTYPE(3)
  /INTERCEPT=INCLUDE
  /POSTHOC=OC (TUKEY)
  /EMMEANS=TABLES(OC)
  /PRINT=ETASQ HOMOGENEITY DESCRIPTIVE
  /CRITERIA=ALPHA(.05)
  /DESIGN=OC.
```

Levene's Test of Equality of Error Variances[a]

Dependent Variable: PER

F	df1	df2	Sig.
1.192	4	1061	.313

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.

a. Design: Intercept + OC

Tests of Between-Subjects Effects

Dependent Variable: PER

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	8.155[a]	4	2.039	3.473	.008	.013
Intercept	1.374	1	1.374	2.341	.126	.002
OC	8.155	4	2.039	3.473	.008	.013

Error	622.810	1061	.587
Total	631.354	1066	
Corrected Total	630.965	1065	

a. R Squared = .013 (Adjusted R Squared = .009)

Multiple Comparisons

Dependent Variable: PER

Tukey HSD

		Mean Difference			95% Confidence Interval	
(I) OC	(J) OC	(I-J)	Std. Error	Sig.	Lower Bound	Upper Bound
1.000	2.000	-.3246	.12630	.077	-.6698	.0205
	3.000	-.2257	.12844	.399	-.5767	.1253
	4.000	-.3663	.15490	.126	-.7895	.0570
	5.000	-.4108*	.13386	.019	-.7765	-.0450
2.000	1.000	.3246	.12630	.077	-.0205	.6698
	3.000	.0990	.05567	.387	-.0532	.2511
	4.000	-.0416	.10293	.994	-.3229	.2396
	5.000	-.0861	.06723	.703	-.2698	.0976
3.000	1.000	.2257	.12844	.399	-.1253	.5767
	2.000	-.0990	.05567	.387	-.2511	.0532
	4.000	-.1406	.10555	.671	-.4290	.1478
	5.000	-.1851	.07118	.071	-.3796	.0094
4.000	1.000	.3663	.15490	.126	-.0570	.7895
	2.000	.0416	.10293	.994	-.2396	.3229
	3.000	.1406	.10555	.671	-.1478	.4290
	5.000	-.0445	.11207	.995	-.3507	.2617
5.000	1.000	.4108*	.13386	.019	.0450	.7765
	2.000	.0861	.06723	.703	-.0976	.2698
	3.000	.1851	.07118	.071	-.0094	.3796
	4.000	.0445	.11207	.995	-.2617	.3507

Based on observed means.

The error term is Mean Square(Error) = .587.

*. The mean difference is significant at the .05 level.

Regression for PER

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT PER
  /METHOD=ENTER ZO ZA ZC ZE ZN.
```

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.171[a]	.029	.025	.76014	.029	6.397	5	1060	.000

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-.018	.023		-.782	.434
	Zscore(O)	-.060	.031	-.072	-1.954	.051
	Zscore(A)	.019	.028	.023	.657	.511
	Zscore(C)	.014	.028	.017	.509	.611
	Zscore(E)	.049	.030	.062	1.641	.101
	Zscore(N)	-.115	.029	-.142	-3.956	.000

a. Dependent Variable: PER

```
REGRESSION
 /MISSING LISTWISE
 /STATISTICS COEFF OUTS R ANOVA CHANGE
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT PER
 /METHOD=ENTER CPROB1 CPROB2 CPROB3 CPROB4.
```

Model Summary

Model	R	R Square	Change Statistics

			Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.117[a]	.014	.011	.76548	.014	4.934	3	1062	.002

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.023	.044		.512	.609
	CPROB1	.100	.097	.037	1.032	.302
	CPROB2	-.369	.136	-.084	-2.714	.007
	CPROB4	-.106	.075	-.050	-1.411	.159

a. Dependent Variable: PER

```
REGRESSION
 /MISSING LISTWISE
 /STATISTICS COEFF OUTS R ANOVA CHANGE
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT PER
 /METHOD=ENTER OC1 OC2 OC3 OC4.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.114[a]	.013	.009	.76616	.013	3.473	4	1061	.008

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.092	.057		1.616	.106
	OClass 1 dummy variable	-.411	.134	-.101	-3.069	.002

	OClass 2 dummy variable	-.086	.067	-.055	-1.281	.200
	OClass 3 dummy variable	-.185	.071	-.110	-2.600	.009
	OClass 4 dummy variable	-.044	.112	-.014	-.397	.691

a. Dependent Variable: PER

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT PER
  /METHOD=ENTER OCPROB1 OCPROB2 OCPROB3 OCPROB4 OCPROB5.
```

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.122[a]	.015	.011	.76537	.015	4.029	4	1061	.003

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-.093	.052		-1.784	.075
	OCPROB1	-.327	.161	-.068	-2.038	.042
	OCPROB2	.102	.077	.046	1.326	.185
	OCPROB4	.151	.140	.035	1.077	.282
	OCPROB5	.197	.083	.080	2.376	.018

a. Dependent Variable: PER

Hierarchical regression for PER Dimensions

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT ZTAD
  /METHOD=ENTER ZO ZA ZC ZE ZN
  /METHOD=ENTER OC1 OC2 OC3 OC4.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.173[a]	.030	.026	.95887509	.030	6.575	5	1060	.000
2	.187[b]	.035	.027	.95824028	.005	1.351	4	1056	.249

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-.002	.030		-.075	.941
	Zscore(O)	-.041	.039	-.039	-1.065	.287
	Zscore(A)	-.077	.036	-.074	-2.156	.031
	Zscore(C)	.049	.035	.046	1.391	.164
	Zscore(E)	.082	.038	.082	2.175	.030
	Zscore(N)	-.138	.037	-.136	-3.786	.000
2	(Constant)	-.026	.129		-.204	.838
	Zscore(O)	-.069	.048	-.066	-1.444	.149
	Zscore(A)	-.072	.040	-.070	-1.829	.068
	Zscore(C)	.062	.045	.059	1.369	.171
	Zscore(E)	.088	.044	.087	1.985	.047
	Zscore(N)	-.135	.043	-.132	-3.146	.002
	OClass 1 dummy variable	-.273	.317	-.053	-.860	.390
	OClass 2 dummy variable	.021	.123	.010	.167	.868

OClass 3 dummy variable	.045	.203	.021	.222	.824
OClass 4 dummy variable	.191	.202	.046	.949	.343

a. Dependent Variable: Zscore(TAD)

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT ZTAD
  /METHOD=ENTER ZO ZA ZC ZE ZN
  /METHOD=ENTER OCPROB1 OCPROB2 OCPROB3 OCPROB4 OCPROB5.
```

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change
1	.173[a]	.030	.026	.95887509	.030	6.575	5	1060	.000
2	.196[b]	.038	.030	.95653737	.008	2.297	4	1056	.057

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT ZLM
  /METHOD=ENTER ZO ZA ZC ZE ZN
  /METHOD=ENTER OC1 OC2 OC3 OC4.
```

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change
1	.105[a]	.011	.006	.95341695	.011	2.365	5	1060	.038
2	.120[b]	.014	.006	.95360543	.003	.895	4	1056	.466

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.030	.029		1.010	.313
	Zscore(O)	-.034	.039	-.033	-.883	.378
	Zscore(A)	-.005	.035	-.004	-.128	.898
	Zscore(C)	.006	.035	.006	.183	.855
	Zscore(E)	.051	.038	.052	1.359	.175
	Zscore(N)	-.084	.036	-.083	-2.307	.021
2	(Constant)	-.071	.128		-.557	.577
	Zscore(O)	-.039	.048	-.038	-.829	.408
	Zscore(A)	.009	.039	.008	.218	.828
	Zscore(C)	.019	.045	.019	.433	.665
	Zscore(E)	.066	.044	.067	1.506	.132
	Zscore(N)	-.096	.043	-.095	-2.235	.026
	OClass 1 dummy variable	-.047	.315	-.009	-.148	.883
	OClass 2 dummy variable	.105	.122	.054	.854	.393
	OClass 3 dummy variable	.155	.202	.074	.765	.444
	OClass 4 dummy variable	.212	.201	.052	1.056	.291

a. Dependent Variable: Zscore(LM)

```
REGRESSION
 /MISSING LISTWISE
 /STATISTICS COEFF OUTS R ANOVA CHANGE
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT ZLM
 /METHOD=ENTER ZO ZA ZC ZE ZN
 /METHOD=ENTER OCPROB1 OCPROB2 OCPROB3 OCPROB4 OCPROB5.
```

Model Summary

Model	R	R Square	Change Statistics

			Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.105[a]	.011	.006	.95341695	.011	2.365	5	1060	.038
2	.129[b]	.017	.008	.95247504	.006	1.524	4	1056	.193

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT ZIR
  /METHOD=ENTER ZO ZA ZC ZE ZN
  /METHOD=ENTER OC1 OC2 OC3 OC4.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.190[a]	.036	.032	.92050593	.036	7.935	5	1060	.000
2	.199[b]	.039	.031	.92062625	.003	.931	4	1056	.445

Coefficients[a]

		Unstandardized Coefficients		Standardized Coefficients		
Model		B	Std. Error	Beta	t	Sig.
1	(Constant)	-.041	.028		-1.425	.154
	Zscore(O)	.097	.037	.096	2.616	.009
	Zscore(A)	-.025	.034	-.025	-.723	.470
	Zscore(C)	-.054	.034	-.053	-1.610	.108
	Zscore(E)	.012	.036	.012	.318	.750
	Zscore(N)	-.143	.035	-.146	-4.087	.000
2	(Constant)	-.085	.124		-.691	.490
	Zscore(O)	.079	.046	.078	1.722	.085
	Zscore(A)	-.020	.038	-.020	-.522	.602
	Zscore(C)	-.050	.043	-.050	-1.160	.246
	Zscore(E)	.016	.042	.016	.366	.714
	Zscore(N)	-.145	.041	-.147	-3.509	.000

OClass 1 dummy variable	-.191	.304	-.039	-.626	.531
OClass 2 dummy variable	.060	.118	.032	.507	.612
OClass 3 dummy variable	.058	.195	.028	.296	.767
OClass 4 dummy variable	.144	.194	.036	.744	.457

a. Dependent Variable: Zscore(IR)

```
REGRESSION
 /MISSING LISTWISE
 /STATISTICS COEFF OUTS R ANOVA CHANGE
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT ZIR
 /METHOD=ENTER ZO ZA ZC ZE ZN
 /METHOD=ENTER OCPROB1 OCPROB2 OCPROB3 OCPROB4 OCPROB5.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.190[a]	.036	.032	.92050593	.036	7.935	5	1060	.000
2	.205[b]	.042	.034	.91946289	.006	1.602	4	1056	.172

```
REGRESSION
 /MISSING LISTWISE
 /STATISTICS COEFF OUTS R ANOVA CHANGE
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT ZLeads
 /METHOD=ENTER ZO ZA ZC ZE ZN
 /METHOD=ENTER OC1 OC2 OC3 OC4.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.217[a]	.047	.042	.97223246	.047	10.428	5	1060	.000

2	.243[b]	.059	.051	.96788611	.012	3.385	4	1056	.009

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-.025	.030		-.838	.402
	Zscore(O)	-.186	.039	-.172	-4.722	.000
	Zscore(A)	.057	.036	.054	1.592	.112
	Zscore(C)	.035	.036	.032	.978	.328
	Zscore(E)	.130	.038	.127	3.393	.001
	Zscore(N)	-.130	.037	-.124	-3.508	.000
2	(Constant)	-.054	.130		-.413	.680
	Zscore(O)	-.217	.048	-.201	-4.492	.000
	Zscore(A)	.072	.040	.069	1.812	.070
	Zscore(C)	.022	.046	.020	.484	.628
	Zscore(E)	.148	.045	.144	3.324	.001
	Zscore(N)	-.140	.043	-.134	-3.221	.001
	OClass 1 dummy variable	-.474	.320	-.091	-1.481	.139
	OClass 2 dummy variable	.008	.124	.004	.067	.947
	OClass 3 dummy variable	.128	.205	.059	.626	.531
	OClass 4 dummy variable	.054	.204	.013	.266	.791

a. Dependent Variable: Zscore(Leads)

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT ZLeads
  /METHOD=ENTER ZO ZA ZC ZE ZN
  /METHOD=ENTER OCPROB1 OCPROB2 OCPROB3 OCPROB4 OCPROB5.
```

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.217[a]	.047	.042	.97223246	.047	10.428	5	1060	.000
2	.248[b]	.061	.053	.96667482	.014	4.056	4	1056	.003

```
REGRESSION
 /MISSING LISTWISE
 /STATISTICS COEFF OUTS R ANOVA CHANGE
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT ZBDCR
 /METHOD=ENTER ZO ZA ZC ZE ZN
 /METHOD=ENTER OC1 OC2 OC3 OC4.
```

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.246[a]	.061	.056	.95088717	.061	13.688	5	1060	.000
2	.253[b]	.064	.056	.95092091	.003	.981	4	1056	.417

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	-.044	.029		-1.504	.133
	Zscore(O)	-.086	.038	-.081	-2.225	.026
	Zscore(A)	.270	.035	.259	7.637	.000
	Zscore(C)	-.013	.035	-.012	-.361	.718
	Zscore(E)	-.051	.038	-.050	-1.360	.174
	Zscore(N)	-.051	.036	-.049	-1.399	.162
2	(Constant)	.084	.128		.657	.511
	Zscore(O)	-.135	.047	-.127	-2.840	.005

Zscore(A)	.252	.039	.242	6.406	.000
Zscore(C)	-.026	.045	-.024	-.577	.564
Zscore(E)	-.075	.044	-.074	-1.723	.085
Zscore(N)	-.022	.043	-.022	-.523	.601
OClass 1 dummy variable	-.526	.314	-.102	-1.671	.095
OClass 2 dummy variable	-.104	.122	-.052	-.849	.396
OClass 3 dummy variable	-.217	.201	-.102	-1.077	.282
OClass 4 dummy variable	-.045	.200	-.011	-.223	.823

a. Dependent Variable: Zscore(BDCR)

```
REGRESSION
 /MISSING LISTWISE
 /STATISTICS COEFF OUTS R ANOVA CHANGE
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT ZBDCR
 /METHOD=ENTER ZO ZA ZC ZE ZN
 /METHOD=ENTER OCPROB1 OCPROB2 OCPROB3 OCPROB4 OCPROB5.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.246[a]	.061	.056	.95088717	.061	13.688	5	1060	.000
2	.253[b]	.064	.056	.95105179	.003	.908	4	1056	.458

```
REGRESSION
 /MISSING LISTWISE
 /STATISTICS COEFF OUTS R ANOVA CHANGE
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT ZGC
 /METHOD=ENTER ZO ZA ZC ZE ZN
 /METHOD=ENTER OC1 OC2 OC3 OC4.
```

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.136[a]	.019	.014	.95508129	.019	4.011	5	1060	.001
2	.139[b]	.019	.011	.95656456	.001	.179	4	1056	.949

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	.034	.029		1.143	.253
	Zscore(O)	-.032	.039	-.031	-.829	.407
	Zscore(A)	-.001	.035	-.001	-.027	.979
	Zscore(C)	.062	.035	.059	1.767	.077
	Zscore(E)	.019	.038	.019	.512	.609
	Zscore(N)	-.112	.036	-.111	-3.088	.002
2	(Constant)	-.022	.128		-.167	.867
	Zscore(O)	-.026	.048	-.024	-.535	.593
	Zscore(A)	.010	.040	.009	.243	.808
	Zscore(C)	.066	.045	.064	1.473	.141
	Zscore(E)	.033	.044	.033	.750	.453
	Zscore(N)	-.124	.043	-.123	-2.898	.004
	OClass 1 dummy variable	.044	.316	.009	.138	.891
	OClass 2 dummy variable	.040	.123	.020	.324	.746
	OClass 3 dummy variable	.114	.203	.054	.561	.575
	OClass 4 dummy variable	.059	.201	.015	.296	.768

a. Dependent Variable: Zscore(GC)

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA CHANGE
```

```
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT ZGC
 /METHOD=ENTER ZO ZA ZC ZE ZN
 /METHOD=ENTER OCPROB1 OCPROB2 OCPROB3 OCPROB4 OCPROB5.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.136[a]	.019	.014	.95508129	.019	4.011	5	1060	.001
2	.149[b]	.022	.014	.95509866	.004	.990	4	1056	.412

```
REGRESSION
 /MISSING LISTWISE
 /STATISTICS COEFF OUTS R ANOVA CHANGE
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT ZIT
 /METHOD=ENTER ZO ZA ZC ZE ZN
 /METHOD=ENTER OC1 OC2 OC3 OC4.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.128[a]	.016	.012	.93742413	.016	3.505	5	1060	.004
2	.137[b]	.019	.010	.93795630	.003	.699	4	1056	.592

Coefficients[a]

		Unstandardized Coefficients		Standardized Coefficients		
Model		B	Std. Error	Beta	t	Sig.
1	(Constant)	-.129	.029		-4.459	.000
	Zscore(O)	-.072	.038	-.070	-1.902	.057
	Zscore(A)	.038	.035	.038	1.083	.279
	Zscore(C)	-.045	.034	-.044	-1.306	.192
	Zscore(E)	.040	.037	.041	1.077	.282
	Zscore(N)	-.104	.036	-.105	-2.904	.004
2	(Constant)	-.143	.126		-1.137	.256

Zscore(O)	-.086	.047	-.084	-1.836	.067
Zscore(A)	.044	.039	.044	1.144	.253
Zscore(C)	-.050	.044	-.049	-1.130	.259
Zscore(E)	.048	.043	.049	1.106	.269
Zscore(N)	-.108	.042	-.109	-2.572	.010
OClass 1 dummy variable	-.207	.310	-.042	-.669	.504
OClass 2 dummy variable	.006	.120	.003	.049	.961
OClass 3 dummy variable	.058	.199	.028	.290	.772
OClass 4 dummy variable	.028	.197	.007	.143	.886

a. Dependent Variable: Zscore(IT)

```
REGRESSION
 /MISSING LISTWISE
 /STATISTICS COEFF OUTS R ANOVA CHANGE
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT ZIT
 /METHOD=ENTER ZO ZA ZC ZE ZN
 /METHOD=ENTER OCPROB1 OCPROB2 OCPROB3 OCPROB4 OCPROB5.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.128[a]	.016	.012	.93742413	.016	3.505	5	1060	.004
2	.149[b]	.022	.014	.93638444	.006	1.589	4	1056	.175

```
REGRESSION
 /MISSING LISTWISE
 /STATISTICS COEFF OUTS R ANOVA CHANGE
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT ZEC
 /METHOD=ENTER ZO ZA ZC ZE ZN
 /METHOD=ENTER OC1 OC2 OC3 OC4.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.184[a]	.034	.029	.97823901	.034	7.438	5	1060	.000
2	.185[b]	.034	.026	.97987336	.000	.117	4	1056	.977

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.031	.030		1.025	.306
	Zscore(O)	-.065	.040	-.060	-1.640	.101
	Zscore(A)	.012	.036	.012	.339	.735
	Zscore(C)	-.019	.036	-.018	-.543	.587
	Zscore(E)	.035	.039	.034	.907	.364
	Zscore(N)	-.190	.037	-.182	-5.107	.000
2	(Constant)	.020	.132		.153	.879
	Zscore(O)	-.072	.049	-.067	-1.481	.139
	Zscore(A)	.013	.040	.013	.332	.740
	Zscore(C)	-.011	.046	-.011	-.247	.805
	Zscore(E)	.037	.045	.036	.812	.417
	Zscore(N)	-.189	.044	-.181	-4.301	.000
	OClass 1 dummy variable	-.056	.324	-.011	-.174	.862
	OClass 2 dummy variable	.009	.126	.004	.070	.944
	OClass 3 dummy variable	.015	.208	.007	.070	.944
	OClass 4 dummy variable	.081	.206	.019	.395	.693

a. Dependent Variable: Zscore(EC)

```
REGRESSION
 /MISSING LISTWISE
```

```
/STATISTICS COEFF OUTS R ANOVA CHANGE
/CRITERIA=PIN(.05) POUT(.10)
/NOORIGIN
/DEPENDENT ZEC
/METHOD=ENTER ZO ZA ZC ZE ZN
/METHOD=ENTER OCPROB1 OCPROB2 OCPROB3 OCPROB4 OCPROB5.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.184[a]	.034	.029	.97823901	.034	7.438	5	1060	.000
2	.187[b]	.035	.027	.97946286	.001	.338	4	1056	.852

```
REGRESSION
 /MISSING LISTWISE
 /STATISTICS COEFF OUTS R ANOVA CHANGE
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT ZOWD
 /METHOD=ENTER ZO ZA ZC ZE ZN
 /METHOD=ENTER OC1 OC2 OC3 OC4.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.186[a]	.035	.030	.95439205	.035	7.593	5	1060	.000
2	.205[b]	.042	.034	.95249277	.007	2.058	4	1056	.084

Coefficients[a]

		Unstandardized Coefficients		Standardized Coefficients		
Model		B	Std. Error	Beta	t	Sig.
1	(Constant)	-.018	.029		-.627	.531
	Zscore(O)	-.122	.039	-.116	-3.168	.002
	Zscore(A)	-.103	.035	-.100	-2.914	.004
	Zscore(C)	.107	.035	.101	3.051	.002
	Zscore(E)	.125	.038	.124	3.311	.001
	Zscore(N)	-.079	.036	-.077	-2.161	.031

2	(Constant)	-.325	.128		-2.545	.011
	Zscore(O)	-.084	.048	-.080	-1.769	.077
	Zscore(A)	-.063	.039	-.061	-1.601	.110
	Zscore(C)	.138	.045	.131	3.062	.002
	Zscore(E)	.173	.044	.173	3.954	.000
	Zscore(N)	-.127	.043	-.125	-2.985	.003
	OClass 1 dummy variable	.414	.315	.081	1.315	.189
	OClass 2 dummy variable	.299	.122	.153	2.448	.015
	OClass 3 dummy variable	.481	.202	.228	2.384	.017
	OClass 4 dummy variable	.401	.200	.098	2.004	.045

a. Dependent Variable: Zscore(OWD)

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT ZOWD
  /METHOD=ENTER ZO ZA ZC ZE ZN
  /METHOD=ENTER OCPROB1 OCPROB2 OCPROB3 OCPROB4 OCPROB5.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.186[a]	.035	.030	.95439205	.035	7.593	5	1060	.000
2	.209[b]	.044	.036	.95165920	.009	2.524	4	1056	.039

Appendix G

NB. C = Profile, C1 = Organization-based Categorical Profile 1, CPROB1 = Organization-based Continuous Profile 1, OC1 = Occupation-based Categorical Profile 1, OCPROB1 = Occupation-based Continuous Profile 1, PER = Overall Performance, TAD = Thinks and Acts Decisively, LM = Leverages Mastery, IR = Innovates and Reapplies, BDCR = Builds Diverse, Collaborative Relationships, GC = Grows Capability, IT = In Touch, EC = Embraces Change, OWD = Operates with Discipline, Z added before a variable's name refers to a standardized variable in the form of z-score.

One-way ANOVA for PER

```
UNIANOVA PER BY OC
  /METHOD=SSTYPE(3)
  /INTERCEPT=INCLUDE
  /POSTHOC=OC (TUKEY)
  /EMMEANS=TABLES(OC)
  /PRINT=ETASQ HOMOGENEITY DESCRIPTIVE
  /CRITERIA=ALPHA(.05)
  /DESIGN=OC.
```

Levene's Test of Equality of Error Variances[a]

Dependent Variable: PER

F	df1	df2	Sig.
1.413	4	863	.228

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.[a]

a. Design: Intercept + OC

Tests of Between-Subjects Effects

Dependent Variable: PER

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	15.526[a]	4	3.882	6.709	.000	.030
Intercept	.086	1	.086	.148	.701	.000

OC	15.526	4	3.882	6.709	.000	.030
Error	499.293	863	.579			
Total	517.021	868				
Corrected Total	514.819	867				

a. R Squared = .030 (Adjusted R Squared = .026)

Multiple Comparisons

Dependent Variable: PER

Tukey HSD

					95% Confidence Interval	
(I) OC	(J) OC	Mean Difference (I-J)	Std. Error	Sig.	Lower Bound	Upper Bound
1.000	2.000	-.1339	.21607	.972	-.7245	.4568
	3.000	.2802*	.09897	.038	.0096	.5507
	4.000	-.1441	.06097	.127	-.3107	.0226
	5.000	-.2129	.08004	.061	-.4317	.0059
2.000	1.000	.1339	.21607	.972	-.4568	.7245
	3.000	.4140	.22829	.366	-.2100	1.0381
	4.000	-.0102	.21457	1.000	-.5968	.5763
	5.000	-.0790	.22074	.996	-.6825	.5244
3.000	1.000	-.2802*	.09897	.038	-.5507	-.0096
	2.000	-.4140	.22829	.366	-1.0381	.2100
	4.000	-.4243*	.09564	.000	-.6857	-.1628
	5.000	-.4931*	.10879	.000	-.7905	-.1957
4.000	1.000	.1441	.06097	.127	-.0226	.3107
	2.000	.0102	.21457	1.000	-.5763	.5968
	3.000	.4243*	.09564	.000	.1628	.6857
	5.000	-.0688	.07588	.894	-.2762	.1386
5.000	1.000	.2129	.08004	.061	-.0059	.4317
	2.000	.0790	.22074	.996	-.5244	.6825
	3.000	.4931*	.10879	.000	.1957	.7905
	4.000	.0688	.07588	.894	-.1386	.2762

Based on observed means.

The error term is Mean Square(Error) = .579.

*. The mean difference is significant at the .05 level.

Regression for PER

```
REGRESSION
 /MISSING LISTWISE
 /STATISTICS COEFF OUTS R ANOVA CHANGE
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT PER
 /METHOD=ENTER ZO ZA ZC ZE ZN.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.221[a]	.049	.043	.75368	.049	8.865	5	862	.000

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.071	.026		2.715	.007
	Zscore(O)	-.017	.034	-.021	-.495	.621
	Zscore(A)	-.032	.031	-.041	-1.037	.300
	Zscore(C)	.018	.029	.021	.597	.550
	Zscore(E)	.118	.032	.156	3.641	.000
	Zscore(N)	-.089	.033	-.116	-2.697	.007

a. Dependent Variable: PER

```
REGRESSION
 /MISSING LISTWISE
 /STATISTICS COEFF OUTS R ANOVA CHANGE
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT PER
 /METHOD=ENTER CPROB1 CPROB2 CPROB3 CPROB4.
```

Model Summary

Model	R	R Square	Change Statistics

			Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.201[a]	.040	.037	.75619	.040	12.103	3	864	.000

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.183	.049		3.764	.000
	CPROB1	-.001	.105	.000	-.005	.996
	CPROB2	-.561	.113	-.172	-4.960	.000
	CPROB4	-.261	.084	-.121	-3.121	.002

a. Dependent Variable: PER

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT PER
  /METHOD=ENTER OC1 OC2 OC3 OC4.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.174[a]	.030	.026	.76063	.030	6.709	4	863	.000

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.190	.065		2.918	.004
	OClass 1 dummy variable	-.213	.080	-.127	-2.660	.008
	OClass 2 dummy variable	-.079	.221	-.012	-.358	.720

	OClass 3 dummy variable	-.493	.109	-.181	-4.532	.000
	OClass 4 dummy variable	-.069	.076	-.044	-.907	.365

a. Dependent Variable: PER

```
REGRESSION
 /MISSING LISTWISE
 /STATISTICS COEFF OUTS R ANOVA CHANGE
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT PER
 /METHOD=ENTER OCPROB1 OCPROB2 OCPROB3 OCPROB4 OCPROB5.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.198[a]	.039	.035	.75709	.039	8.793	4	863	.000

Coefficients[a]

		Unstandardized Coefficients		Standardized Coefficients		
Model		B	Std. Error	Beta	t	Sig.
1	(Constant)	.157	.050		3.133	.002
	OCPROB1	-.219	.087	-.098	-2.508	.012
	OCPROB2	-.033	.237	-.005	-.140	.889
	OCPROB3	-.524	.109	-.169	-4.831	.000
	OCPROB5	.048	.098	.019	.488	.626

a. Dependent Variable: PER

Hierarchical regression for PER Dimensions

```
REGRESSION
 /MISSING LISTWISE
 /STATISTICS COEFF OUTS R CHANGE
 /CRITERIA=PIN(.05) POUT(.10)
```

```
/NOORIGIN
/DEPENDENT ZTAD
/METHOD=ENTER ZO ZA ZC ZE ZN
/METHOD=ENTER OC1 OC2 OC3 OC4.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.222[a]	.049	.044	.92736828	.049	8.942	5	862	.000
2	.240[b]	.057	.048	.92552486	.008	1.859	4	858	.116

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.113	.032		3.532	.000
	Zscore(O)	.061	.042	.062	1.465	.143
	Zscore(A)	-.077	.038	-.079	-2.029	.043
	Zscore(C)	.032	.036	.032	.880	.379
	Zscore(E)	.077	.040	.084	1.946	.052
	Zscore(N)	-.131	.040	-.140	-3.244	.001
2	(Constant)	-.224	.147		-1.529	.127
	Zscore(O)	.113	.051	.115	2.245	.025
	Zscore(A)	-.043	.044	-.044	-.974	.330
	Zscore(C)	.042	.039	.042	1.098	.273
	Zscore(E)	.138	.049	.149	2.792	.005
	Zscore(N)	-.195	.049	-.209	-3.969	.000
	OClass 1 dummy variable	.539	.218	.262	2.467	.014
	OClass 2 dummy variable	.226	.311	.029	.727	.467
	OClass 3 dummy variable	.593	.332	.177	1.787	.074
	OClass 4 dummy variable	.307	.137	.161	2.243	.025

a. Dependent Variable: Zscore(TAD)

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT ZTAD
  /METHOD=ENTER ZO ZA ZC ZE ZN
  /METHOD=ENTER OCPROB1 OCPROB2 OCPROB3 OCPROB4 OCPROB5.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.222[a]	.049	.044	.92736828	.049	8.942	5	862	.000
2	.229[b]	.053	.043	.92788738	.003	.759	4	858	.552

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT ZLM
  /METHOD=ENTER ZO ZA ZC ZE ZN
  /METHOD=ENTER OC1 OC2 OC3 OC4.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.213[a]	.045	.040	.95747116	.045	8.190	5	862	.000
2	.227[b]	.052	.042	.95659482	.006	1.395	4	858	.234

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-.008	.033		-.237	.813
	Zscore(O)	-.069	.043	-.068	-1.604	.109
	Zscore(A)	-.055	.039	-.055	-1.402	.161

	Zscore(C)	.019	.037	.018	.506	.613
	Zscore(E)	.178	.041	.186	4.332	.000
	Zscore(N)	-.097	.042	-.101	-2.332	.020
2	(Constant)	-.169	.152		-1.115	.265
	Zscore(O)	-.058	.052	-.057	-1.110	.267
	Zscore(A)	-.051	.045	-.051	-1.124	.261
	Zscore(C)	.012	.040	.011	.292	.770
	Zscore(E)	.194	.051	.204	3.806	.000
	Zscore(N)	-.125	.051	-.129	-2.453	.014
	OClass 1 dummy variable	.261	.226	.123	1.156	.248
	OClass 2 dummy variable	-.005	.322	-.001	-.016	.987
	OClass 3 dummy variable	.090	.343	.026	.264	.792
	OClass 4 dummy variable	.179	.142	.091	1.267	.206

a. Dependent Variable: Zscore(LM)

```
REGRESSION
 /MISSING LISTWISE
 /STATISTICS COEFF OUTS R CHANGE
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT ZLM
 /METHOD=ENTER ZO ZA ZC ZE ZN
 /METHOD=ENTER OCPROB1 OCPROB2 OCPROB3 OCPROB4 OCPROB5.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.213[a]	.045	.040	.95747116	.045	8.190	5	862	.000
2	.233[b]	.055	.045	.95508040	.009	2.080	4	858	.081

```
REGRESSION
 /MISSING LISTWISE
 /STATISTICS COEFF OUTS R CHANGE
```

```
/CRITERIA=PIN(.05) POUT(.10)
/NOORIGIN
/DEPENDENT ZIR
/METHOD=ENTER ZO ZA ZC ZE ZN
/METHOD=ENTER OC1 OC2 OC3 OC4.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.239[a]	.057	.052	.91838222	.057	10.474	5	862	.000
2	.252[b]	.064	.054	.91735656	.006	1.482	4	858	.206

Coefficients[a]

		Unstandardized Coefficients		Standardized Coefficients		
Model		B	Std. Error	Beta	t	Sig.
1	(Constant)	.199	.032		6.271	.000
	Zscore(O)	.074	.041	.075	1.801	.072
	Zscore(A)	-.102	.038	-.105	-2.697	.007
	Zscore(C)	-.041	.036	-.041	-1.141	.254
	Zscore(E)	.125	.039	.135	3.169	.002
	Zscore(N)	-.114	.040	-.122	-2.848	.005
2	(Constant)	-.028	.145		-.191	.849
	Zscore(O)	.097	.050	.099	1.941	.053
	Zscore(A)	-.075	.044	-.077	-1.720	.086
	Zscore(C)	-.033	.038	-.033	-.862	.389
	Zscore(E)	.160	.049	.174	3.268	.001
	Zscore(N)	-.151	.049	-.163	-3.105	.002
	OClass 1 dummy variable	.378	.216	.185	1.746	.081
	OClass 2 dummy variable	.304	.309	.039	.984	.325
	OClass 3 dummy variable	.291	.329	.087	.884	.377
	OClass 4 dummy variable	.211	.136	.111	1.553	.121

a. Dependent Variable: Zscore(IR)

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT ZIR
  /METHOD=ENTER ZO ZA ZC ZE ZN
  /METHOD=ENTER OCPROB1 OCPROB2 OCPROB3 OCPROB4 OCPROB5.
```

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.239[a]	.057	.052	.91838222	.057	10.474	5	862	.000
2	.251[b]	.063	.053	.91772073	.006	1.311	4	858	.264

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT ZLeads
  /METHOD=ENTER ZO ZA ZC ZE ZN
  /METHOD=ENTER OC1 OC2 OC3 OC4.
```

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.219[a]	.048	.043	.94635909	.048	8.712	5	862	.000
2	.239[b]	.057	.047	.94401320	.009	2.072	4	858	.083

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	.047	.033		1.438	.151
	Zscore(O)	-.110	.042	-.109	-2.598	.010

	Zscore(A)	.040	.039	.040	1.028	.304
	Zscore(C)	.014	.037	.014	.379	.705
	Zscore(E)	.188	.041	.200	4.647	.000
	Zscore(N)	-.061	.041	-.064	-1.484	.138
2	(Constant)	-.075	.150		-.502	.616
	Zscore(O)	-.109	.052	-.108	-2.118	.034
	Zscore(A)	.021	.045	.021	.467	.641
	Zscore(C)	-.009	.039	-.009	-.232	.817
	Zscore(E)	.189	.050	.200	3.747	.000
	Zscore(N)	-.082	.050	-.086	-1.629	.104
	OClass 1 dummy variable	.153	.223	.073	.686	.493
	OClass 2 dummy variable	-.267	.318	-.034	-.841	.401
	OClass 3 dummy variable	-.049	.338	-.014	-.144	.886
	OClass 4 dummy variable	.190	.140	.097	1.359	.175

a. Dependent Variable: Zscore(Leads)

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT ZLeads
  /METHOD=ENTER ZO ZA ZC ZE ZN
  /METHOD=ENTER OCPROB1 OCPROB2 OCPROB3 OCPROB4 OCPROB5.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.219[a]	.048	.043	.94635909	.048	8.712	5	862	.000
2	.243[b]	.059	.049	.94311810	.011	2.484	4	858	.042

REGRESSION

```
/MISSING LISTWISE
/STATISTICS COEFF OUTS R CHANGE
/CRITERIA=PIN(.05) POUT(.10)
/NOORIGIN
/DEPENDENT ZBDCR
/METHOD=ENTER ZO ZA ZC ZE ZN
/METHOD=ENTER OC1 OC2 OC3 OC4.
```

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change
1	.193[a]	.037	.032	.94611567	.037	6.641	5	862	.000
2	.212[b]	.045	.035	.94449300	.008	1.741	4	858	.139

Coefficients[a]

Model		Unstandardized Coefficients: B	Std. Error	Standardized Coefficients: Beta	t	Sig.
1	(Constant)	.062	.033		1.882	.060
	Zscore(O)	-.023	.042	-.023	-.540	.589
	Zscore(A)	.157	.039	.159	4.035	.000
	Zscore(C)	-.026	.037	-.026	-.713	.476
	Zscore(E)	.037	.041	.040	.923	.356
	Zscore(N)	-.052	.041	-.055	-1.266	.206
2	(Constant)	-.159	.150		-1.060	.289
	Zscore(O)	.001	.052	.001	.020	.984
	Zscore(A)	.152	.045	.154	3.384	.001
	Zscore(C)	-.041	.039	-.040	-1.033	.302
	Zscore(E)	.061	.050	.065	1.209	.227
	Zscore(N)	-.092	.050	-.097	-1.831	.067
	OClass 1 dummy variable	.273	.223	.131	1.223	.222
	OClass 2 dummy variable	-.121	.318	-.015	-.380	.704
	OClass 3 dummy variable	.262	.339	.077	.774	.439

OClass 4 dummy variable	.277	.140	.143	1.983	.048

a. Dependent Variable: Zscore(BDCR)

```
REGRESSION
 /MISSING LISTWISE
 /STATISTICS COEFF OUTS R CHANGE
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT ZBDCR
 /METHOD=ENTER ZO ZA ZC ZE ZN
 /METHOD=ENTER OCPROB1 OCPROB2 OCPROB3 OCPROB4 OCPROB5.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.193[a]	.037	.032	.94611567	.037	6.641	5	862	.000
2	.218[b]	.047	.037	.94320930	.010	2.330	4	858	.054

```
REGRESSION
 /MISSING LISTWISE
 /STATISTICS COEFF OUTS R CHANGE
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT ZGC
 /METHOD=ENTER ZO ZA ZC ZE ZN
 /METHOD=ENTER OC1 OC2 OC3 OC4.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.165[a]	.027	.022	.96051194	.027	4.846	5	862	.000
2	.178[b]	.032	.021	.96066034	.004	.933	4	858	.444

Coefficients[a]

	Unstandardized Coefficients		Standardized Coefficients		
Model	B	Std. Error	Beta	t	Sig.

1	(Constant)	.048	.033		1.436	.152
	Zscore(O)	.007	.043	.007	.161	.872
	Zscore(A)	-.071	.040	-.071	-1.790	.074
	Zscore(C)	.068	.038	.066	1.818	.069
	Zscore(E)	.118	.041	.125	2.875	.004
	Zscore(N)	-.042	.042	-.044	-1.007	.314
2	(Constant)	-.090	.152		-.594	.553
	Zscore(O)	.007	.052	.007	.136	.892
	Zscore(A)	-.068	.046	-.068	-1.489	.137
	Zscore(C)	.063	.040	.061	1.584	.114
	Zscore(E)	.127	.051	.134	2.475	.014
	Zscore(N)	-.057	.051	-.060	-1.126	.261
	OClass 1 dummy variable	.147	.227	.070	.646	.518
	OClass 2 dummy variable	.226	.323	.028	.700	.484
	OClass 3 dummy variable	.105	.344	.031	.306	.760
	OClass 4 dummy variable	.191	.142	.098	1.346	.179

a. Dependent Variable: Zscore(GC)

```
REGRESSION
 /MISSING LISTWISE
 /STATISTICS COEFF OUTS R CHANGE
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT ZGC
 /METHOD=ENTER ZO ZA ZC ZE ZN
 /METHOD=ENTER OCPROB1 OCPROB2 OCPROB3 OCPROB4 OCPROB5.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.165[a]	.027	.022	.96051194	.027	4.846	5	862	.000
2	.185[b]	.034	.024	.95931915	.007	1.536	4	858	.190

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT ZIT
  /METHOD=ENTER ZO ZA ZC ZE ZN
  /METHOD=ENTER OC1 OC2 OC3 OC4.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.119[a]	.014	.009	.96096202	.014	2.491	5	862	.030
2	.127[b]	.016	.006	.96233418	.002	.386	4	858	.819

Coefficients[a]

		Unstandardized Coefficients		Standardized Coefficients		
Model		B	Std. Error	Beta	t	Sig.
1	(Constant)	.071	.033		2.151	.032
	Zscore(O)	-.027	.043	-.027	-.637	.524
	Zscore(A)	-.040	.040	-.041	-1.017	.309
	Zscore(C)	.016	.038	.015	.418	.676
	Zscore(E)	.074	.041	.079	1.802	.072
	Zscore(N)	-.077	.042	-.081	-1.844	.066
2	(Constant)	-.082	.153		-.540	.589
	Zscore(O)	-.009	.053	-.009	-.165	.869
	Zscore(A)	-.031	.046	-.031	-.671	.503
	Zscore(C)	.016	.040	.016	.405	.685
	Zscore(E)	.097	.051	.103	1.880	.060
	Zscore(N)	-.104	.051	-.109	-2.025	.043
	OClass 1 dummy variable	.207	.227	.099	.913	.361
	OClass 2 dummy variable	.111	.324	.014	.344	.731

OClass 3 dummy variable	.248	.345	.073	.719	.472
OClass 4 dummy variable	.167	.142	.086	1.175	.240

a. Dependent Variable: Zscore(IT)

```
REGRESSION
 /MISSING LISTWISE
 /STATISTICS COEFF OUTS R CHANGE
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT ZIT
 /METHOD=ENTER ZO ZA ZC ZE ZN
 /METHOD=ENTER OCPROB1 OCPROB2 OCPROB3 OCPROB4 OCPROB5.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.119[a]	.014	.009	.96096202	.014	2.491	5	862	.030
2	.132[b]	.017	.007	.96165051	.003	.692	4	858	.598

```
REGRESSION
 /MISSING LISTWISE
 /STATISTICS COEFF OUTS R CHANGE
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT ZEC
 /METHOD=ENTER ZO ZA ZC ZE ZN
 /METHOD=ENTER OC1 OC2 OC3 OC4.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.211[a]	.045	.039	.93993780	.045	8.069	5	862	.000
2	.217[b]	.047	.037	.94085347	.003	.581	4	858	.677

Coefficients[a]

Model	Unstandardized Coefficients	Standardized Coefficients	t	Sig.

		B	Std. Error	Beta		
1	(Constant)	.029	.033		.896	.370
	Zscore(O)	-.015	.042	-.015	-.357	.721
	Zscore(A)	-.021	.039	-.021	-.541	.588
	Zscore(C)	-.021	.037	-.020	-.567	.571
	Zscore(E)	.093	.040	.099	2.301	.022
	Zscore(N)	-.154	.041	-.163	-3.766	.000
2	(Constant)	-.171	.149		-1.144	.253
	Zscore(O)	.010	.051	.010	.203	.839
	Zscore(A)	.002	.045	.003	.056	.956
	Zscore(C)	-.011	.039	-.011	-.281	.779
	Zscore(E)	.126	.050	.135	2.516	.012
	Zscore(N)	-.187	.050	-.197	-3.732	.000
	OClass 1 dummy variable	.277	.222	.133	1.247	.213
	OClass 2 dummy variable	.330	.316	.042	1.043	.297
	OClass 3 dummy variable	.380	.337	.112	1.127	.260
	OClass 4 dummy variable	.198	.139	.103	1.425	.154

a. Dependent Variable: Zscore(EC)

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT ZEC
  /METHOD=ENTER ZO ZA ZC ZE ZN
  /METHOD=ENTER OCPROB1 OCPROB2 OCPROB3 OCPROB4 OCPROB5.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.211[a]	.045	.039	.93993780	.045	8.069	5	862	.000

2	.218[b]	.048	.038	.94069087	.003	.655	4	858	.623

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT ZOWD
  /METHOD=ENTER ZO ZA ZC ZE ZN
  /METHOD=ENTER OC1 OC2 OC3 OC4.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.222[a]	.049	.044	.92658974	.049	8.916	5	862	.000
2	.224[b]	.050	.040	.92829511	.001	.209	4	858	.934

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.075	.032		2.353	.019
	Zscore(O)	-.048	.042	-.049	-1.157	.248
	Zscore(A)	-.120	.038	-.123	-3.149	.002
	Zscore(C)	.098	.036	.097	2.698	.007
	Zscore(E)	.167	.040	.181	4.218	.000
	Zscore(N)	-.068	.040	-.073	-1.682	.093
2	(Constant)	-.045	.147		-.308	.758
	Zscore(O)	-.029	.051	-.030	-.576	.565
	Zscore(A)	-.109	.044	-.112	-2.482	.013
	Zscore(C)	.100	.039	.099	2.594	.010
	Zscore(E)	.189	.050	.204	3.801	.000
	Zscore(N)	-.091	.049	-.097	-1.839	.066
	OClass 1 dummy variable	.182	.219	.088	.829	.408
	OClass 2 dummy variable	.068	.312	.009	.219	.827

OClass 3 dummy variable	.219	.333	.066	.660	.510
OClass 4 dummy variable	.116	.137	.061	.844	.399

a. Dependent Variable: Zscore(OWD)

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT ZOWD
  /METHOD=ENTER ZO ZA ZC ZE ZN
  /METHOD=ENTER OCPROB1 OCPROB2 OCPROB3 OCPROB4 OCPROB5.
```

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.222[a]	.049	.044	.92658974	.049	8.916	5	862	.000
2	.224[b]	.050	.040	.92834194	.001	.187	4	858	.945