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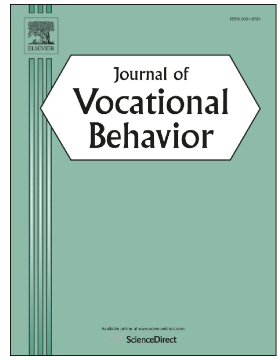

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Vocational Interest Profiles: Profile Replicability and Relations with the STEM Major Choice and the Big-Five

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Abstract

Normative circular and dimensional models are the dominant structures for the organization of vocational interests in the scientific literature. However, it is increasingly recognized that not all individuals' interest configurations can be adequately represented by normative models. Adopting a person-centered, multidimensional perspective on vocational interests, the current study seeks to identify distinct profiles of interests based on RIASEC data that integrate interest configurations that align with and deviate from normal circular and dimensional structures. We also test the replicability of the profile structure, examine the likelihood of STEM degree choice as a function of profile membership, and investigate core personality predictors of interest profile membership. Latent profile analyses revealed six profiles of vocational interests, representing distinct combinations of the RIASEC interests (i.e., social-dominant, disinterested, high realistic-dominant, investigative-dominant, ambivalent, and conventional-dominant), which replicated entirely across independent subsamples. Furthermore, the profiles differed on the likelihood of STEM degree choice, with the conventional-dominant profile evincing the highest probability of choice and the social-dominant profile evincing the lowest probability of choice. Finally, results revealed that the Big-Five personality traits were differentially related to interest profile membership, largely in line with vocational interest theory. The present findings constitute novel evidence that a person-centered framework for the representation of interest configurations can accommodate both people's adherence to and deviations from normative structures for the organization of interests. The findings also underpin the use of all available interest information on individuals, rather than reliance on the two or three highest interest dimensions, to inform educational and vocational decision-making.

Keywords: vocational interests; interest profiles; STEM career choices; academic and career choices; latent profile analysis; profile invariance; profile similarity

Vocational Interest Profiles: Profile Replicability and Relations with STEM Major Choice and the Big-Five

Australia, and several other industrialized nations, require an extensive science, technology, engineering, and mathematics (STEM) workforce for economic prosperity, productivity, and global competitiveness. However, the demand for people in STEM outweighs the supply of STEM-trained individuals. One reason for this supply-demand issue is a decline in the proportion of students choosing STEM-related pathways (Ainley, Kos, & Nicholas, 2008; McIlveen & Perera, 2016). In response to this concern, bourgeoning research has been devoted to identifying predictors of STEM educational and career choices (Shoffner & Dockery, 2015). Among the determinants examined is vocational interests, which is unsurprising, given not only theory positing a central role of interests in choice behaviors (Lent, Brown, & Hackett, 1994) but also extant evidence demonstrating that interests predict choices (Gasser, Larson, & Borgen, 2007; Larson, Wu, Bailey, Borgen, & Gasser, 2010; Päßler & Hell, 2012). However, existing research, with few exceptions (Leuty, Hansen, & Speaks, 2016; McLarnon, Carswell, & Schneider, 2015), is limited to investigating the unique and additive relations of interests with choices from a variable-centered perspective. This approach assumes that individuals in a sample are from the same population and share the same set of parameters, disregarding the potential existence of multiple latent subpopulations that may show distinct configurations of interests. The near-exclusive focus on unique relations is problematic given work showing that individuals may simulatenaouly endorse multiple interests (McLarnon et al., 2015; Strahan & Severinghaus, 1992; Tay, Su, & Rounds, 2011). From a social cognitive perspective on the career choice process, such interest combinations may be more important for people's educational and vocational choices than interests in isolation and may be a truer representation of individuals' interest profiles, which themselves emerge, in part, from people's dispositional characteristics. However, only little research has been conducted to determine how interests can be combined, and even less is known about how these combinations predict individuals' choices and are predicted by theoretically-meaningful antecedents in the career choice process, such as personality dispositions.

Drawing on vocational interest theory and social cognitive perspectives, this article reports on research conducted to identify latent profiles of vocational interests based on RIASEC data and examine the associations of interest profile membership with STEM major choice and core personality traits. First, we use latent profile analysis (LPA) to identify profiles of vocational interests, representing qualitatively and quantitatively distinct interest combinations. We then test the replicability of the retained profiles using multiple-group tests of latent profile solution similarity. Third, based on social cognitive perspectives of career choice processes, we examine whether the vocational interest profiles differ with respect to the probability of enrolment in a STEM degree program. Results of significant interest-profile-choice relations would serve as validity evidence underpinning the expected profiles. Finally, as these integrative theories of career development posit that person inputs, such as core dispositions, play a role in the interest-choice process, we investigate the Big-Five personality dimensions as theoretically plausible predictors of interest profile membership (Schaub & Tokar, 1997). Findings of meaningful personality-interest-profile relations would provide further validity evidence for the profiles.

Theoretical Underpinning

Holland's (1997) theory of vocational interests and work environments is the dominant model of vocational interest structure, positing the existence of six vocational interests. The interests are positioned along the vertices of an equilateral hexagon in a R-I-A-S-E-C configuration, which is functionally equivalent to the arrangement of the interests at equidistant points around a circumplex. The relative distance between each of these vertices reflects the conceptual correspondence between the interests. This structural representation implies a prototypical configuration of relative interest levels within individuals (Gurtman & Pincus, 2003). For example, individuals with dominant realistic interests are expected to be relatively lower on the investigative and conventional domains, even lower on the artistic and enterprising domains, and lowest on the social domain. Individuals' interest profiles are believed to reflect this general pattern of RIASEC relations implied by proximities (Nagy, Trautwein, & Lüdtke, 2010).

The pattern of relations among the six interests is also reflected in Prediger's model (Prediger, 1982), which posits that two bipolar dimensions—people-things and data-ideas—account for the relations among the six domains. A central tenet of Prediger's (1982) conceptualization is the bipolarity of opposite interest dimensions. Bipolarity implies the mutual exclusivity of opposite interest dimensions; that is, high levels on any interest dimension precludes the possibility of high scores on an opposite interest dimension. Indeed, the bipolarity tenet implies that there should be a strong, if not perfect, negative correlation between opposite interest domains. Conceptually, the bipolarity principle suggests that individuals may be interested in people-or-things-based work-tasks but not both; likewise, people may be interested in data or ideas but not both (Prediger, 1982). In Prediger's model, the things-people axis intersects the circumplex at the vertices of the hexagon on which the realistic and social domains are positioned. This indicates that a preference for realistic activities and work environments precludes interests in social activities and environments. Notably, the bipolarity of these dimensions assumes that lower realistic interests reflect higher levels of social interests (Goh & Leong, 1993).

Notwithstanding the acceptance of the bipolarity principle, evidence suggests that the assumption may be untenable. First, correlations between the opposite interest dimensions are consistently shown to deviate from the expected strong, negative coefficients required to infer bipolarity (Mount, Barrick, Scullen, & Rounds, 2005), with associations ranging from small and negative to small and positive (Tay et al., 2011). The magnitude of associations is indicative of relative independence of the opposite dimensions rather than bipolarity. Second, using ideal-point latent trait models, Tay, Drasgow, Rounds, and Williams (2009) showed that individuals often reported interests in (a) people and things and (b) data and idea, positioning these individuals at the center of the purported dimensional continua, which is indicative of the possession of dual interests. These findings were underpinned by recent results showing that over 50% of large samples of armed forces personnel and community dwellers possessed interests in both people and things (viz., social and realistic interests) (Tay et al., 2011). Furthermore, Tay et al. (2011) found that measurement models positing bipolarity of the opposite interest dimensions had appreciably worse fit than multidimensional representations. Taken together, this evidence is inconsistent with bipolarity and, instead, supports a bivariate representation of interest configuration. This bivariate perspective holds that individuals may possess interests in both people and things, and data and ideas, which may reflect a truer representation of people's configuration of interests (e.g., bus drivers who may possess interests in practical activities but also have a preference for work involving social interactions). Under the bipolarity assumption, this combination of interests would not be theoretically permissible.

A Multivariate, Person-Centered Approach to Representing Vocational Interests

McLarnon et al. (2015) proposed a multivariate, person-centered extension of Tay et al's (2011) bivariate conceptualization of vocational interests. This approach to representing interest profiles considers the within-person interaction of all RIASEC interests, capturing the complexity of individual profiles of preferences for activities and environments. The person-centered approach is centered on the detection of unobserved population heterogeneity in some construct (e.g., interests). Unobserved heterogeneity refers to the presence of multiple latent subpopulations within a population where subpopulation membership is not known a priori but must be inferred from the data (Lubke & Muthén, 2005). The detection of unobserved heterogeneity is typically accomplished using mixture models, such as LPA models, and is manifested as latent classes or profiles characterized by qualitatively and quantitatively distinct configurations of individual characteristics, such as interests. Thus, the person-centered approach may accommodate the view that individuals can simultaneously endorse several interests, reflected in qualitatively and quantitatively distinct profiles of interest (Leuty et al., 2016; McLarnon et al., 2015). In this regard, the person-centered approach may provide a better representation of interest typologies than traditional Holland codes drawn from only the two or three highest interest dimensions. The person-centered perspective also assumes that distinct configurations of both high and low levels of multiple vocational interests move people towards and away from certain academic and work environments and activities rather than a combination of only those interest for which individuals possess high levels or even still interests uniquely or additively considered. This multivariate, person-centered perspective may be required to sufficiently represent individuals' complete interest profile structures (Sung, Cheng, & Hsueh, 2017).

There is some evidence supporting the existence of qualitatively and quantitatively distinct profiles of vocational interests. Meta-analytic research and recent latent variable analyses show sufficiently weak associations among RIASEC interest dimensions (Tay et al., 2011). The implication of small relations is that levels of no one RIASEC dimension hinge heavily on levels of another dimension. Thus, traits may simultaneously co-exist at different levels within individuals. Consistent with this perspective, evidence for quantitatively and qualitatively distinct profiles of interests has been obtained in two recent person-centered studies. First, using mixture analyses, McLarnon et al. (2015) identified eight-profiles of vocational interests in college students as follows: (a) “realistic-dominant” with comparatively higher scores on the realistic interest than all other interests; (b) “investigative-dominant” with high levels of the investigative interest and low levels on all other interests; (c) “disinterested” with uniformly well-below average interest scores; (d) “weak realistic-dominant”, characterized by the highest levels of realistic but generally less differentiation between interests than the realistic-dominant profile; (e) “neutral” with average levels across all six interests; (f) “entrepreneur” defined by the highest levels of enterprising interest but also moderate levels of social and conventional interests; (g) “artistic-dominant” with considerably higher scores on the artistic interest than all other interests; and (h) the “conventional-business” profile characterized by high levels of enterprising interests, above-average levels of conventional interests, and below average levels of all other interests.

Several profiles identified in McLarnon et al’s (2015) work also emerged in Leuty et al’s (2016) mixture analyses of vocational and leisure interest data in college students. Specifically, artistic-dominant and neutral profiles as well as profiles indicative of vocational disinterest, conventional-business, and weak-realistic dominant were identified. Dissimilar to McLarnon et al. (2015), Leuty et al. identified a social-dominant profile, and there was an absence of a realistic-dominant profile with strong interest differentiation (i.e., scatter). These differences may be attributable to the restriction of Leuty et al’s sample to students in psychology courses who tend to have more social and less realistic interests than what may be typically expected in more heterogeneous college samples (Rosen, Holmberg, & Holland, 1994). Nevertheless, these findings, taken with the emerging person-centered perspective on interests, suggest that student samples will be heterogeneous with respect to interest data (Hypothesis 1 [H1]).

A key issue in person-centered research is the extent to which identified latent profiles replicate across samples drawn from the same population and generalize across distinct populations. This issue of profile replicability and generalizability is not unique to person-centered research, but assumes particular prominence in person-centered analyses in which it is difficult to rule out the possibility of the emergence of spurious latent classes under realistic model conditions (Bauer & Curran, 2004). Set against this problem of spurious profile estimation is the issue of the statistical equivalence between LPA and CFA models. Specifically, a CFA containing k latent factors has identical variance-covariance and mean structure implications as an LPA model with k + 1 latent profiles assuming local independence (Peugh & Fan, 2013). Taken together, these issues underscore the importance of establishing the construct validity of the profiles identified. One approach to validation is to examine profile replicability and/or generalizability (Morin, Meyer, Creusier, & Biétry, 2016). Accordingly, in the present study, we investigate whether the profiles replicate across samples drawn from the sample population using a novel taxonomy of tests of profile replicability in random split halves of the participant sample (Morin et al., 2016). As a randomized split is inherently arbitrary, we expect complete invariance of the profile solution across the subsamples (Hypothesis 2 [H2]).

STEM Major Choice as an Outcome of Interest Profile Membership

Contemporary models of choice processes posit that interest is among the most important factors in choice behaviors (Lent et a., 1994). From this perspective, interests guide and sustain people in their movement towards, or away from, certain activities and environments (Larson, Pesch, Bonitz, Wu, & Werbel, 2014). Consistent with this view, research shows that (a) interests are rated by individuals as the most important factor in educational and career decision-making (Webb, Lubinski, & Benbow, 2002; Tang, 2009) and (b) that interests predict educational and career choices (Ainley et al., 1990; Elsworth et al, 1999), including in STEM-related domains. For instance, evidence shows that individuals with greater realistic interests are more likely to choose technical and mechanical educational pathways, including engineering (Larson et al., 2010; Päßler & Hell, 2012; Ralston, Borgen, Rottinghaus, & Donnay, 2004), and much less likely to choose programs in the humanities and social sciences (Päßler & Hell, 2012). This research also demonstrates that greater investigative and enterprising interests predict a higher likelihood of choosing math and science academic programs (Ainley et al., 1990; Lapan, Shaughnessy, & Boggs, 1996; Päßler & Hell, 2012; Ralston et al., 2004). Indeed, recent evidence shows that college students' levels of investigative interests differentiates whether these students graduate with science majors (Larson et al., 2014). Research also shows associations of conventional interests with choices of educational programs in computing studies and information technology (Elsworth et al., 1999; Larson et al., 2010). On the contrary, there is evidence that individuals with high social and artistic interests are less likely to choose STEM pathways (Päßler & Hell, 2012; Ralston et al., 2004). These findings, while important initial steps in understanding the role of interests in choice behaviors, only provide a partial picture of the way in which interests guide choice behavior.

Although consistent with career development theories (Holland, 1996; Lent et al., 1994), extant findings from variable-centered work do not to account for the possibility that individuals may simultaneously endorse more than one interest (McLarnon et al., 2015; Strahan & Severinghaus, 1992; Tay et al., 2011). Indeed, individuals' interest combinations, by virtue of better representing patterns of likes, dislikes, and indifferences towards activities and environments, may be more important for their selection of STEM pathways, than interests in isolation. Investigating how vocational interests combine to influence STEM choice outcomes may provide a more complete understanding of the role of interests in STEM choice outcomes. This focus would seem more important now than ever as industrialized nations struggle to attract people into STEM careers to meet the demands for workers in STEM fields. Accordingly, the present research seeks to extend these findings from variable-centered investigations by examining whether vocational interest profiles, reflecting distinct configurations of the RIASEC interests, differ with respect to the probability of matriculating in a STEM major. Based on prior variable-centered work, we expect the probability of STEM major choice to be higher in profiles characterized by greater levels of realistic, conventional, and investigative interests, and lower artistic and social interests (Hypothesis 3 [H3]).

Big-Five Personality Predictors of Interest Profile Membership

Integrative models of career development, such as the social cognitive career theory (Lent et al., 2002), hold that personal inputs, such as core personality dispositions, influence vocational interests in the choice process (Schuab & Tokar, 2005). From this perspective, personality precedes interests, guiding the selection of learning experience that allow for the shaping and refining of interests (Schaub & Toker, 2005). Consistent with this view, research shows a consistent pattern of robust associations between the Big-Five and the RIASEC interests as follows: (a) openness with artistic interests; (b) openness with investigative interests; (c) extraversion with enterprising interests; (d) agreeableness with social interests (e) extraversion with social interests; and (f) conscientiousness with conventional interests (Barrick et al., 2003; De Fruyt & Mervielde, 1997; Larson, Rottinghuas, & Borgen, 2002). However, a limitation of this research is the focus on the unique and additive relations of the Big-Five dimensions with the vocational interests, which only provides partial understanding of personality-trait-vocational-interest relations. Indeed, this research does not consider the way in which core personality dimensions may be related to distinct combinations of vocational interests.

Recent research redresses this limitation by considering relations of personality with latent subgroups characterized by distinct interest configurations. For instance, McLarnon et al. (2015) found that conscientiousness was highest in an “entrepreneur” profile characterized by very high levels of enterprising interests, moderately high levels of conventional and social interests, slightly above-average investigative interests, and below average levels of realistic and artistic interests. Extraversion was lowest in an interest profile characterized by high investigative interests, and below mean levels on all other interests. Leuty et al. (2016) also observed theoretically meaningful differences in personality dimensions across profiles of vocational interests. Neuroticism and openness were highest in an artistic-dominant profile. Openness was lowest in a “competitive-business” profile characterized by high levels of enterprising and conventional interests, near-average levels of realistic, investigative, and social interests, and below-average levels of the artistic interests. Finally, agreeableness was highest in a social-dominant profile.

Although McLarnon et al (2015) and Leuty et al's (2016) work extends prior variable-centered research, the studies are limited insofar as they do not directly examine personality dimensions as predictors of the likelihood of interest profile membership. Instead, these studies examined mean differences in personality as a function of interest profile membership, which is somewhat inconsistent with the view that core dispositions predict interest development (e.g., Schuab & Tokar, 2005). A more theoretically-consistent approach is to examine personality traits as predictors of the probability of interest profile membership. Accordingly, the present research seeks to extend prior work by investigating the Big-Five as predictors of interest profile membership. Based on theory and the evidence reviewed, we expect individuals reporting higher extraversion (Hypothesis 4 [H4]) and agreeableness (Hypothesis 5 [H5]) to have a greater likelihood of membership in profiles in which the social interest is dominant. We also expect individuals with higher conscientiousness to have a greater likelihood of membership in profiles with dominant conventional interests (Hypothesis 6 [H6]). In addition, we predict a greater likelihood of membership in profiles characterized by higher investigative and artistic interests for individuals reporting higher openness (Hypothesis 7 [H7]). Finally, we expect individuals reporting greater extraversion to be more likely to have membership in a profile characterized by higher enterprising interests (Hypothesis 8 [H8]).

Method

Participants and Procedure

Participants were a convenience sample of 764 college students enrolled at a medium-sized Australian university. This initial sample was randomly divided to yield two equal-sized subsamples. The mean age of participants in the first subsample was 31.71 (*SD* = 11.06) and 74.9% (*n* = 286) of the sample was female. Sixteen participants (4.2%) did not report their age, and two participants (0.5%) did not report their gender. Sixty-eight (18.1%) participants were enrolled in STEM majors whereas 286 (74.9%) participants were enrolled in non-STEM majors. To be classified as a STEM major, students had to be enrolled in either science, including mathematical sciences, or engineering and surveying, or information technology programs. Non-STEM majors were those matriculated in education, arts, humanities, and social sciences (e.g., law, business) programs. Eighteen students (4.7%) were enrolled in “other” programs and nine participants (2.4%) did not select a major. For the second subsample, the mean age of participants was 31.94 (SD = 11.47) and 76.7% (n = 293) of the sample was female. Fourteen participants (4.2%) did not report their age, and four participants (1.0%) did not report their gender. Participants were enrolled in STEM (*n* = 68; 17.8%), non-STEM (*n* = 292; 76.4%), or “other” (*n* = 14; 3.7%) programs. Eight (2.1%) participants did not select a major. The mean age in each subsample was consistent with the university’s profile as a provider of higher education to mature-age students, including those undertaking studies by distance education while employed, usually for the purpose of transitioning into a new career or upgrading current professional qualifications. Thus, with many of its students already in the workforce, the range and mean age of the university’s profile tends to be slightly higher than national norms (Australian Government, 2017). The proportion of enrolments in STEM degrees observed in the subsamples (17.8%) was largely consistent with the university’s proportion of enrolments in STEM programs (18.7%).

Measures

RIASEC Interests. The RIASEC interests were assessed using the activity-based Alternative Forms Public Domain RIASEC Marker Scales (RIASEC-Profiler) (Armstrong, Allison, & Rounds, 2008). Each RIASEC dimension is indexed by eight items, which are rated on a five-point Likert-type scale, ranging from 1 (*Strongly Dislike*) to 5 (*Strongly Like*), based on the extent to which participants enjoy performing the work activity reflected in each item. Scores obtained from the measure have been shown to be internally consistent (Armstrong et al., 2008; Armstrong & Vogel, 2009) and structurally valid (Armstrong et al., 2008; Armstrong & Vogel, 2009. In addition, evidence for convergent validity with respect to interests measured using the Strong Interest Inventory (Armstrong et al., 2008) and divergent validity with respect to the Big-Five and HEXACO personality dimensions (McKay & Tokar, 2012) has been obtained. Coefficient alpha reliabilities were uniformly acceptable in subsamples 1 and 2, respectively, for the Realistic ($\alpha = .881$, $\alpha = .905$), Investigative ($\alpha = .907$, $\alpha = .905$), Artistic ($\alpha = .867$, α

= .855), Social (α = .844, α = .818), Enterprising (α = .852, α = .859), and Conventional (α .913, α = .906) scale scores.

Mini-IPIP. The Mini-IPIP (Donnellan, Oswald, Baird, & Lucas, 2006) comprises 20 items designed to measure the Big-Five personality factors. Each factor is indexed by four items, which are rated on a five-point Likert-type scale, ranging from 1 (*very inaccurate*) to 5 (*very accurate*). Scores from the Mini-IPIP have been shown to possess structural (Cooper, Smillie, & Corr, 2010), convergent (Donnellan et al., 2006), and criterion-related validity (Donnellan et al., 2006; Perera, Granziera, & McIlveen, 2017). Score reliability estimates for the dimensions in college samples tend to range from .65 – 80 (Cooper et al., 2010), with the lowest estimates for conscientiousness, neuroticism, and agreeableness. These reliability estimates converge with those obtained in Australian samples (Perera et al., 2017). In the present sample, the coefficient alpha reliabilities for subsamples 1 and 2, respectively, were acceptable for the Extraversion (α = .791, α = .807), Agreeableness (α = .752, α = .720), Conscientiousness (α = .653, α = .626), Neuroticism (α = .701, α = .644), and Intellect/Imagination (α = .678, α = .710) scale scores.[1]

Statistical Analyses

Analyses were conducted in four phases. In phase one, preliminary multiple-group confirmatory factor analyses (CFA) of the RIASEC data across the subsamples were conducted to obtain factor scores on the interest dimensions from the most invariant measurement model to serve as LPA indicators. Factor score mixture indicators should be preferred to non-refined scale scores for four reasons: (a) factor score indicators give greater weight to more reliable items and, in this regard, provide partial control for errors of measurement; (b) factor scores are also typically based on standardized information, thereby

[1] Cronbach’s alpha will vary with the number of items. Alpha will increase with increasing items even while keeping the average inter-item correlation constant. This property of alpha disadvantages shorter scales. In addition, short form measures, such as the Mini-IPIP, contain only a few items designed to represent fairly heterogonous domain-level personality constructs, which may also result in lower internal consistency estimates. Taken together, a small number of items and content heterogeneity is the probable cause of the seemingly lower internal consistency estimates in the present study. However, an application of the Spearman-Brown prophecy formula to the existing estimates and scale length shows that the reliability estimate for conscientiousness, for instance, would be .788, with an increase of even 2 items. For this reason, the reliabilities reported herein are reasonable with respect to scale length.

facilitating profile labeling and interpretability; (c) factor-scores based on complex CFA models accommodate construct-relevant multidimensionality due to item fallibility (Perera, 2015), and, (d) RIASEC-profile factor scores obtained from multiple-group models of invariance ensure the comparability of the interest scores across the independent samples (Morin et al., 2016; Perera & McIlveen, 2017).

For the six-factor CFA models across the subsamples, each RIASEC-Profiler item was specified to load onto one of the six interest dimensions per the a priori scoring key. In addition, items 44, 23 and 22, and 29 were free to cross-load on the Realistic, Artistic, and Conventional factors, respectively, to account for construct-relevant multidimensionality in the item scores due to their purported fallibility as purely unidimensional indicators (Perera, 2016; Perera, McIlveen, Burton, & Corser, 2015). For instance, Item 44 ("Make a map of the bottom of an ocean"), which is primarily designed to index the investigative interest, may also index realistic interests to the extent that it involves practical problems and solutions. Indeed, "geographer", involving study of the earth's surface, is classified under the Realistic interest in the O*NET database.[2] Correlations among the factors were constrained to equality within each of the adjacent (i.e., RI, IA, AS, SE, EC, and CR), distal (i.e., RA, AE, ER, IS, SC, and CI), and opposite (RS, IE, and AC) interest domains as this more parsimonious structure has been shown to provide a better representation of interest data than the model with freely estimated interest relations (Iliescu, Ispas, Ilie, & Ion, 2013). Conditional on the acceptable fit of the six-factor measurement structures in each subsample, we examined the invariance of the RIASEC data across the samples. These multiple-group invariance tests were conducted in line with Millsap and Yun-Tein's (2004) taxonomy of invariance tests, involving the sequential testing of configural invariance, and the invariance of item factor loadings, thresholds,

[2] Item 23 ("Operate a beauty salon or barber shop") and Item 22 ("Teach an individual an exercise routine"), which primarily index the enterprising interest and social interest, respectively, were also specified to load on the artistic interest as the items reflects activities that permit creative expression in visual and performing arts environments. Item 29 ("Manage a department within a large company"), which is designed to index the enterprising interest, was also specified to load on the conventional interest. In addition to tapping a preference for leadership related to the enterprising interest, the item reflects working in a department within a larger company, which may be considered, at least in part, a preference for routine activities in structured work environments. The failure to account for these theoretically-defensible cross-loadings can lead to the inflation of factor correlation estimates (see e.g., Perera, 2015; Perera & Ganguly, 2016) as construct relevant item multidimensionality, which should be modeled via cross-loadings, is absorbed via factor correlations (see e.g., Perera, 2015; Perera & Ganguly, 2016).

uniquenesses, factor variances and covariances, and factor means (Perera, McIlveen, Burton, & Corser, 2015).

Analyses of the preliminary measurement structure were conducted using Mplus 7.4 (Muthén & Muthén, 1998-2015). Solutions were estimated using robust diagonal weighted least squares, with a mean-and-variance-adjusted test statistic, operationalized as the weighted least square mean-variance adjusted (WLSMV) estimator in Mplus. Fit assessment was inclusive and involved an evaluation of fit indices, parameter estimates, and alternative models. As the χ^2 can be oversensitive to minor model misspecifications given even moderate-sized samples and contains a restrictive hypothesis test (i.e., exact fit), three approximate fit indices were considered: RMSEA, < .050 and .080 for close and reasonable fit; Comparative fit index (CFI) and Tucker-Lewis Index (TLI), > .900 and .950 for acceptable and excellent fit, respectively (Marsh, Hau, & Wen, 2007). For nested model comparisons, because the adjusted χ^2 difference (MD $\Delta\chi^2$) test appropriate for the WLSMV estimator also tends to be sensitive to even trivial differences, changes in the CFI (ΔCFI) and RMSEA (ΔRMSEA) were primarily used. A decrease in the CFI and increase in the RMSEA of less than .010 and .015, respectively, are indicative of support for a more restrictive model (Chen, 2007; Cheung & Rensvold, 2002).

Phase two of the analyses involved LPA with the factor scores obtained from the most invariant CFA model of the RIASEC-Profiler data serving as mixture indicators. LPA is a statistical technique for modeling unobserved population heterogeneity. Specifically, LPA models assume that samples drawn from a heterogeneous population generate data that are a mixture of k profile-specific distributions where k is the number of profiles (k > 1) (Peugh & Fan, 2013). LPA models capture heterogeneity by grouping individuals into latent "classes" or "profiles" based on similarities in their response variable data. Accordingly, LPA is an adequate statistical model for modeling heterogeneity in vocational interest data. The LPA models were initially tested separately in each subsample to determine if the same number of profiles could be identified. We estimated models including one to nine profiles based on previous studies suggesting the existence of seven or eight interest profiles (McLarnon et al., 2015; Leuty et al., 2016). Across the models, means of the profile indicators were freely estimated, but indicator variances were equality constrained across the profiles consistent with the homogeneity assumption of the classical LPA model (Lubke & Neale, 2006).

The third phase of the analyses involved tests of the cross-sample replicability of the profile solutions. These tests of profile similarity were conducted in line with the taxonomy of LPA similarity tests proposed by Morin et al. (2016), comprising sequential and comparative tests of configural similarity, structural similarity, dispersion similarity, and distributional similarity. Configural similarity can be inferred from the single-sample LPA tests to the degree that the sample-specific analytic solutions converge in the number of profiles identified. However, configural similarity also requires the simultaneous estimation of the retained *k*-profile model in both groups, which serves as a baseline model against which the more restrictive profile similarity models are compared. From the multi-group model of configural similarity, the model of structural similarity can be tested via constraining the within-profile indicator means to equality across the groups. Conditional on support for structural similarity, dispersion similarity can be examined by imposing equality constraints on the indicator variances across groups, thereby providing tests of the equality of the within-profile variability of the indicators across samples. Finally, the model of distributional similarity requires additive equality restrictions imposed on the class probabilities across group, testing whether the relative sizes of the profiles are equal across groups (Morin et al., 2016).

The LPA analyses were performed using robust maximum likelihood (MLR) estimation in Mplus 7.4 (Muthén & Muthén, 1998-2015). The single-group models were estimated using 3000 random sets of start values with 100 iterations each and the 100 best solutions retained for final stage optimization. These values were increased to 10000, 500, and 500, respectively, for the multiple-group models (Morin et al., 2016). An inclusive approach to single-group model selection was used, involving an evaluation of the theoretical consistency of the solutions and statistical indices, including information criteria and the Bootstrap Likelihood Ratio Test (BLRT) (Henson, Reise, & Kim, 2007; Nylund, Asparouhov, & Muthén, 2007). Specifically, the Bayesian Information Criterion (BIC), the sample-adjusted BIC (Sa-BIC), and the consistent Akaike Information Criterion (CAIC) were used with lower values on the criteria indicative of a better-fitting model (Henson et al., 2007). We also report the Akaike Information Criteria for information purposes. The BLRT provides a test of a *k*-profile model against a *k*-1 profile model, with a non-significant *p*-value indicating that a more parsimonious *k*-1 profile model should be retained. In addition to these statistical indices, we report the entropy values for the models tested, with higher values indicative of greater classification precision. However, it is increasingly recognized that entropy alone should not be used for class enumeration and model selection (Lubke & Muthén, 2007). Finally, for comparative tests of the multiple-group models of LPA similarity, as the models within the similarity taxonomy are nested, the BIC, SaBIC, and CAIC were used (Lubke & Neale, 2008; Morin et al., 2016), with lower values indicative of a better fitting model. As per Morin et al. (2016), profile similarity is inferred if at least two information criteria suggest support for a more parsimonious model.

Conditional on support for at least structural similarity of the LPA solution, and assuming at least strict measurement invariance of the RIASEC-Profiler data, we combined the subsamples for the conduct of tests of the relations of profile membership with STEM major choice and the personality dimensions to avoid sparse cells. The test of the relations of interest profile membership with the binary STEM major choice outcome was implemented via the DCAT function in Mplus (Lanza, Tan, & Bray, 2013). The DCAT function provides equality tests of class-specific probabilities of the distal outcome across the latent profiles without including the outcome directly in the LPA model, thereby ensuring the stability of the initial profile solution. Participants reporting “other” programs and those who did no select a major were not included in the analyses of profile-outcome relations. The predictive relations of personality with interest profile membership were estimated using the auxiliary R3STEP procedure implemented in Mplus (Asparouhov & Muthén, 2014). This procedure first computes the LPA solution using only the mixture indictors. Following this, the most likely class memberships are obtained from the posterior probabilities of the LPA as well as an indicator of profile misclassification. Finally, the most likely latent class is regressed on the covariates while accounting for classification uncertainty in a multinomial logistic model.

Results

Descriptives and Preliminary Measurement Models

Tests of the correlated-six-factor CFA models of the RIASEC-Profiler data resulted in an acceptable fit in both the first, χ^2 (1073) = 2590.72, $p < .001$, CFI = .913, TLI = .908, RMSEA = .061 (90% CI = .058, .064), and second, χ^2 (1073) = 2600.56, $p < .001$, CFI = .903, TLI = .898, RMSEA = .061 (90% CI = .058, .064) subsamples. For the first subsample, all six factors were well-defined with largely moderate-to-strong and uniformly significant loadings (λ = .32–.91, *M* = .71). Similarly, in the second subsample, the six interest dimensions were defined well, with largely moderate-to-strong and uniformly significant loadings (λ = .27–.90, *M* = .71). The complete loading matrices for the six-factor CFA solutions in each sample are provided in Supplemental Appendix A. Given the acceptable fit, we proceeded with the multiple-group invariance tests.

Test statistics and fit indices for the invariance models are shown in Supplemental Appendix B. The model of configural invariance provided an acceptable fit to the data. Support was also found for the invariance of the item loadings, thresholds, uniquenesses, factor variance-covariance matrix, and factor means. Taken together, these results support the complete factorial invariance of scores on the RIASEC-Profiler across the subsamples. Factor scores from this completely invariant solution were saved for use as the mixture indicators in the LPA models. Table 1 shows the means, standard deviations, and correlations for the RIASEC interest factor scores for each subsample as well as the Big-Five personality dimensions.

(Table 1)

Latent Profile Analyses

Table 2 shows indices of fit and classification accuracy for the LPA solutions in each of the subsamples. In the first subsample, the SaBIC continued to decrease with the addition of profiles. The CAIC reached its lowest level for the six-profile solution. In addition, the BIC reached a plateau at six-profiles, after which the decrease for the seven profile solution was minimal and was followed by increases with the addition of profiles. The BLRT was not helpful in the selection of the optimal solution. Classification accuracy of the six-profile solution was reasonable as indexed by the solution entropy value. Average posterior probabilities of class membership in the target profile ranged from .782 to .934 (*M* = .852), with generally low cross probabilities (.000 – .116; *M* = .029).

(Table 2)

For the second subsample, the SaBIC continued to decrease with the addition of profiles (see Table 2). The CAIC and BIC continued to decrease to seven and eight profiles, respectively; however, they reached a plateau at six profiles, after which decreases were minimal with the addition of profiles. Again, the BLRT was not helpful in selecting the optimal solution. The six profile solution showed reasonable classification accuracy. In addition, average posterior probabilities of class membership in the target profiles were generally high, ranging from .782-.956 (M = .854), and cross-probabilities were generally low, ranging from .000-.118 (*M* = .029).

Across both samples, the six profile solutions were theoretically congruous and converged with prior research. Indeed, the six-profile solutions yielded multiple profiles that converge with several subgroups obtained in prior work, including the “investigative dominant”, “realistic dominant”, “disinterested”, “ambivalent”, and “social-dominant” profiles (McLarnon et al., 2015; Leuty et al., 2016). This presence of qualitatively and quantitatively distinct profiles of interests support H1, suggesting the presence of heterogeneity within college students with respect to vocational interest data. Based on these findings, the six-profile solutions were retained in both samples, which is suggestive of the configural similarity of the model.

Cross-Sample Latent Profile Similarity

Given that the same number of profiles was retained in the subsamples, we proceeded with the multiple-group LPA similarity tests to formally examine the cross-subsample replicability of the six-profile solution. Table 2 shows the fit indices for the tests of these profile-similarity models. A multiple-group six-profile model was first simultaneously estimated in both subsamples to serve as the baseline configural similarity model against which the more restrictive similarity models were compared. Relative to this baseline model, the more restrictive structural similarity model resulted in lower values on the BIC, SaBIC, and CAIC, thereby supporting the structural similarity of the six-profile solution across the subsamples. Support was also found for the model of dispersion similarity, with lower values on the BIC, SaBIC, and CAIC relative to the structural similarity solution. Finally, the model of distributional similarity, which, compared with the dispersion similarity solution, had lower values on the BIC, SaBIC, and CAIC, was supported. Taken together, and consistent with H2, the profile similarity tests support the equality of, (a) the number of latent profiles, (b) within-profile mean levels of the mixture indicators, (c) profile indicator variances, and (d) the relative sizes of the latent profiles across the subsamples.

There was a reasonable level of classification accuracy in the retained distributional similarity model (entropy = .828), suggesting that the six profiles are reasonably well demarcated. The six profiles from the final multiple-group distributional similarity solution are shown in Figure 1. The first profile, constituting 19.9% of the subsamples, is characterized by the highest levels of social interest followed by the enterprising interest, and near-mean levels of the artistic interest. This profile also comprised below-average levels of realistic, investigative, and conventional interests. We labeled this profile "social-dominant". The second profile, constituting 10.7% of the subsamples, is characterized by well-below average levels of all six interests. This pattern reflects the "disinterested" profile obtained in previous work. Profile 3, constituting 37.8% of the subsamples, was labeled "high realistic-dominant" to reflect the dominance of realistic but above-average elevation of all six interests. Profile 4, constituting 15.1% of the subsamples, was characterized by above-average levels of investigative, slightly above average levels of artistic, slightly below-average levels of realistic and social, and below-average levels of enterprising and conventional. Accordingly, we labeled Profile 4 "investigative-dominant". In Profile 5, constituting 6.8% of the subsamples, scores on all six interests were considerably above mean-levels. We labeled this profile "ambivalent". Finally, Profile 6, constituting 9.7% of the subsamples, is characterized by above-average levels of conventional, about-average realistic, below-average levels of enterprising, and well-below average levels of investigative, artistic, and social interests. This configuration of interests corresponds to a "conventional-dominant" profile.

(Figure 1)

Interest Profile Membership, STEM Major Choice, and the Big-Five

Given support for the distributional similarity of the six-profile solution and earlier findings of complete measurement invariance of the RIASEC-Profiler scores across the subsamples (see Supplemental Appendix B), we combined the samples to investigate (a) the probability of STEM major choice as a function of profile membership and (b) Big-Five personality predictors of interest profile membership. The results of between-profile comparisons on the probabilities of STEM major choice are shown in Table 3. The likelihood of STEM degree choice was highest among conventional-dominant individuals who had a greater than 1 in 2 chance of choosing a STEM major, significantly exceeding the probabilities observed in all other profiles. The likelihood of choosing a STEM major was lowest among social-dominant individuals. These individuals had less than a 1 in 50 chance of choosing a STEM major, which was significantly lower than the probabilities in all but the disinterested profile. In addition, participants in the high realistic dominant profile had about a 1 in 4 chance of choosing a STEM major, which, in addition to significantly exceeding probabilities in the social-dominant profile, significantly exceeded the probability of STEM major choice observed in the disinterested profile. No significant differences in the probability of STEM major choice were found between the investigative-dominant and ambivalent profiles and between these profiles and the disinterested profile. Taken together, these results are consistent with H3, showing that the probability of STEM major choice is highest among profiles characterized by higher conventional, realistic, and investigative interests and lower social and artistic interests.

(Table 3)

Table 4 shows the results of the multinomial logistic regression models predicting profile membership from the Big-Five personality scores operationalized via the auxiliary three-step approach. Consistent with H4, higher scores on extraversion were associated with a greater likelihood of membership in the social-dominant than the conventional-dominant profile. Furthermore, higher scores on extraversion were significantly associated with being less likely to be in the disinterested, high realistic-dominant, conventional-dominant, and investigative-dominant profiles than the ambivalent profile. Notably, the ambivalent profile, while characterized by high levels of all six interests, had the highest levels of enterprising interests, thereby providing partial support to H8. Generally consistent with H5, higher scores on agreeableness were associated with a greater likelihood of membership in the social-dominant profiles than the investigative-dominant, high realistic-dominant, and disinterested profiles, and a decreased likelihood of membership in the disinterested profile relative to the ambivalent profile. Additionally, for agreeableness, higher scores were associated with a greater likelihood of membership in the social-dominant, high realistic dominant, investigative-dominant, and ambivalent profiles than the conventional dominant profile. In line with H6, higher scores on conscientiousness were associated with a greater likelihood of membership in the conventional dominant profiles than the investigative-dominant profile. Higher scores on conscientiousness were also found to be associated with a higher likelihood of membership in the disinterested profile relative to the investigative-dominant profile. Consistent with H7, for openness, higher scores were associated with a greater likelihood of membership in the investigative-dominant profile than the social-dominant, realistic-dominant, and conventional-dominant profiles. Moreover, higher openness scores were associated with a greater likelihood of membership in the disinterested and high realistic-dominant profiles than the conventional-dominant profile. There were no significant effects of neuroticism on profile membership.

(Table 4)

Discussion

This research adds to an emerging literature investigating vocational interests from a person-centered perspective (McLarnon et al., 2015; Leuty et al., 2016; Tay et al., 2011). The research suggests that there is unobserved heterogeneity in college samples with respect to vocational interests, reflected in the identification of six interest profiles characterized by distinct configurations of the RIASEC dimensions. Accordingly, this work replicates extant research showing the presence of distinct vocational interest profiles in college students and extends this work by obtaining evidence for profile replicability. This research also extends prior work by demonstrating, for the first time, that interest profile membership predicts the probability of STEM major choice. Finally, findings of theoretically-plausible predictive relations of the Big-Five traits with interest profile membership replicate and extend previous work and provide further support for the validity of the profile solution. We discuss these results with respect to vocational interest theory and prior research below.

Evidence was obtained for six distinct interest profiles. First, social-dominant and high realistic-dominant profiles were identified, converging with profiles found in previous research defined by the highest levels of social and realistic interests (Leuty et al., 2016; McLarnon et al., 2015). Specifically, the social-dominant configuration aligns with the “socials” profile obtained in Leuty et al. (2016). The high realistic-dominant configuration was also obtained in Leuty et al., and resembles, in part, the realistic-dominant profiles obtained in McLarnon et al. (2015). Notably, across both the social-dominant and high realistic-dominant profiles, the configuration of interests implies an approximate circumplex structure insofar as the relative levels of interests in these profiles roughly correspond to the relative distance between the interests in an approximate circumplex structure (Nagy et al., 2010). Furthermore, these profiles are somewhat consistent with the bipolarity principle implied by dimensional models of vocational interests (Prediger, 1982). Individuals in these profiles possessed relatively high social interests in combination with relatively low levels of the realistic interests and vice versa. However, in the high realistic-dominant profile, levels on all interests, including the social interest, were above mean levels, suggesting that, though individuals high on realistic interests tend to be lower on social interests, in line with the circumplex and bipolarity perspectives, they possess even slightly above-average absolute levels of interests in the social domain, which accords with the multidimensional perspective on interest configuration, holding that people may possess interests in both people and things (McLarnon et al., 2015; Tay et al., 2011).

Evidence was also obtained for investigative-dominant and conventional-dominant profiles. The investigative-dominant profile, converging in terms of shape and scatter with the investigative-dominant profile found in McLarnon et al. (2015), is characterized by well-above average levels of investigative-interests and the lowest levels of enterprising interests. From the perspective of Prediger’s (1982) model, the data-ideas axis intersects the midpoints of conventional and enterprising and investigative and artistic domains. This suggests, indirectly, that a preference for investigative activities and work environments assumes low enterprising interests (Tay et al., 2011), which is consistent with the present profile. The positioning of the data-ideas axis also indirectly implies that a preference for conventional interests assumes low artistic interests (Prediger, 1982). This configuration of relative interest levels is reflected in the conventional-dominant profile, characterized by the highest-levels of conventional interests and the lowest-levels of artistic interests.

Despite the theoretical consistency of these four profiles, two profiles emerged that diverge from normative circular and dimensional models of interest structure. First, similar to McLarnon et al. (2015), a “disinterested” profile emerged with all scores well-below the mean at near-equivalent levels. As McLarnon et al. note, individuals with uniformly low levels on all six interests may be those who have post-modern career interests that are not sufficiently represented in the RIASEC taxonomy. Alternatively, a “low, flat profile” of interests may indicate the contribution of career indecision associated with depressive or anxious cognition (Meldahl & Muchinsky, 1997; Saunders, Peterson, Sampson, & Reardon, 2000). However, the results do not reveal an association of the disinterested profile with neuroticism, which may account for such dysfunctional cognition (Brown & Hirschi, 2013). Additionally, an “ambivalent” profile was obtained, characterized by well-above average levels on all six interests, which converges with the “enthusiasts” profile obtained in Leuty et al. (2016). This profile may capture those who are ebulliently interested in everything but vocationally uncertain and undecided. Indeed, prior work shows that individuals whose interest configurations deviate from normative circular structures, such as those in the ambivalent and disinterested profiles, are more career uncertain and undecided (Tracey & Darcy, 2002). As common career exploration activities and interventions are typically based on normative structures (Holland, 1997), which deviate from the interest configurations that ambivalent and disinterested individuals use to organize their thinking about career-related decisions, these individuals may experience considerable career decision-making difficulty and greater career indecision. Future research would do well to test these propositions. Notably, the results of this study suggest that this multidimensional, person-centered approach to representing vocational interests is sufficiently flexible to unify both the normative circular and dimensional interest structures as well as deviations from this structure for organizing interests under a common framework.

There was an absence of an artistic-dominant profile in this study. This is somewhat surprising as artistic dominant profiles have been obtained in both McLarnon et al. (2015) and Leuty et al. (2016), describing those who possess the highest levels of artistic interests and comparatively lower levels of the remaining interests. Artistic interests reflect preferences for activities that permit creative expression via visual and performing arts environments. These interests have been shown to be higher in individuals participating in artistic disciplines and, to a lesser extent, humanities and psychology, and comparatively lower in individuals participating in math-science, technical and applied, and economics and business in disciplines (Ainley, 1990; Camp & Chartrand, 1992; Elsworth, 1999; Pabler & Hell, 2012; Wischerts & Vorst, 2012). In this study, there was very little representation (1.7% in each subsample) of individuals from creative arts. This very small proportion, taken with comparatively smaller numbers of those in the humanities relative to economics and business and STEM fields, may explain the failure of an artistic-dominant profile to emerge. Certainly, the reasonably small size of the artistic profile in McLarnon et al. (11.6%) could make it more difficult to identify in studies, such as the present one, where there is a smaller number of those in characteristically artistic domains (Patrick et al., 2011). The smaller number of creative arts students in this sample is unsurprising as the university from which students were sampled is a provider of higher education to largely mature-age students who are undertaking studies in the service of transitioning into a new career or upgrading current professional qualifications. These students tend to take professional-training based degrees that are government supported (due to being in a national priority area) and have clear occupational outcomes (e.g., engineering, education, statistics, public health, natural and physical sciences), which tend not to be in the creative arts and humanities.

A key issue in the detection of latent profiles is their replicability across samples drawn from the same population or across meaningful subpopulations. This is especially important for person-centered analyses where ruling out the emergence of spurious profiles is particularly difficult, and profile replicability supports inferences of profile validity (Morin et al., 2016). Support was found for the configural, structural, dispersion, and distributional similarity of the profiles across random subsamples of the original sample. These results suggest, respectively, that across the subsamples (a) the same number of interest profiles were identified, (b) the six profiles were characterized by similar mean levels of indicators, (c) there is comparable interindividual variability around the interest profiles, and (d) the relative frequency of the profiles is equal. Taken together, these profile similarity results support the within-population consistency of the vocational interest profiles and, thus, support profile validity.

Results demonstrate theoretically-informative differences in the probability of STEM major choice as a function of profile membership. Individuals in the high realistic-dominant profile evinced a 1 in 4 chance of STEM major choice, which was significantly higher than the social-dominant and disinterested subgroups. The results suggest that possessing a configuration of interests characterized by predominantly higher levels of realistic, conventional, investigative, and enterprising interests leads to a higher rate of STEM degree choice than possessing lower levels of these interests. This result is consistent with prior variable-centered evidence showing that people with greater realistic, investigative and enterprising, and conventional interests are more likely to choose, respectively, mechanical (Ainley et al., 1990), math and sciences (Ainley et al., 1990), and information technology (Elsworth et al., 1999) programs. For individuals in this profile, a combination of relatively high realistic, investigative, conventional, and enterprising interests, informs the selection of educational programs that prepare them for work environments and activities characterized by practical or hands-on, methodical and analytical, and routine and structured work, which largely define the breadth of STEM work environments.

A notable finding is the highest probability of STEM degree choice in the conventional-dominant profile. This subgroup evinced a greater than 1 in 2 chance of STEM degree choice, which was significantly higher than all other profiles. Although high levels of conventional interests have been implicated in STEM educational choices (Patrick et al., 2011), particularly information technology (Elsworth et al., 1999), it should be noted that the conventional-dominant profile is characterized by average levels of realistic interests and below average levels of investigative interests. These levels of interests seem somewhat inconsistent with previous work showing that high realistic and investigative interests are consistently associated with STEM-related choices (Ainley et al., 1990). However, an important observation is the well-below average levels of artistic and social interests characterizing the conventional-dominant profile. As the RIASEC framework posits a structure of vocational interests that describes both preferences and *aversions* that inform educational and career choices, it may be that the very low levels of artistic and social interests, in combination with the high conventional interest and average realistic interests, foster STEM degree selection. Indeed, prior research has yielded a pattern of findings suggestive of processes of "negative choice" (Elsworth et al., 1999), whereby higher levels of certain interests render individuals less likely to pursue STEM-related educational pathways. Specifically, there is evidence that individuals with higher artistic (Elsworth et al., 1999; Lapan et al., 1996; Päßler & Hell, 2012) and social interests (Ainley et al., 1990; Elsworth et al., 1999) are less likely to choose STEM pathways, perhaps suggesting that very low levels of these interests may facilitate STEM degree selection. This theoretical position regarding processes of aversion from STEM environments is underpinned by the finding that the social-dominant subgroup evinced lower than a 1 in 50 chance of STEM degree choice, which was significantly lower than all but the disinterested profile.

Results also support the validity of the interest profiles by demonstrating plausible differences in profile membership as a function of personality levels. Higher agreeableness was associated with a greater likelihood of membership in the social-dominant profile than the investigative-dominant, disinterested, realistic-dominant, and conventional-dominant profiles. Furthermore, a greater likelihood of membership in this social-dominant relative to the conventional-dominant profile was associated with greater levels of extraversion. These results converge with prior person-centered research showing that agreeableness is highest in interest profiles dominated by the social interest (Leuty et al., 2016), and variable-centered research demonstrating consistent positive associations of agreeableness and extraversion with social interests (Larson et al., 2002; McKay & Tokar, 2012). Higher agreeableness and extraversion were also associated with the greater likelihood of membership in the ambivalent relative to the disinterested profile. Additionally, higher scores on extraversion were associated with a greater likelihood of membership in the ambivalent profile relative to the high realistic-dominant and investigative-dominant profiles. These effects may be attributed to the higher-levels of enterprising and social interests characterizing the ambivalent profile. Indeed, extraversion is consistently associated with enterprising interests in addition to its well-established associations with social interests (Larson et al., 2002). The high energy, adventurousness, and assertiveness of extraverts may foster preferences for commencing, carrying out, and leading novel projects towards attaining business and economic goals. Furthermore, for extraverts, greater dispositional excitement seeking and activity-levels, which underlie basic exploratory tendencies (Peterson, Smith, & Carson, 2002), may foster interest in diverse work activities as reflected in the ambivalent profile.

Further plausible personality-interest-profile relations were obtained. Consistent with expectations, greater openness was associated with a higher likelihood of membership in the investigative-dominant profile than the conventional-dominant and high realistic-dominant profiles. These results are consistent with (a) prior LPA work showing higher levels of openness in profiles characterized by dominant investigative interests (McLarnon et al., 2015) and (b) variable-centered evidence for moderate and positive relations of openness with investigative interests (Larson et al., 2002; McKay & Tokar, 2012). Dispostional preferences for complex problems among those with greater openness may foster the development of interests for methodical and analytic work. A notable result was the association of greater conscientiousness with a higher probability of membership in the disinterested profile than the investigative-dominant profile. Heightened rigidity in those with high levels of conscientiousness may inhibit diverse career exploration activities, leading to greater vocational disinterests relative to possessing an interest configuration characterized by a preference for highly analytic work activities and environments involving creative expression. Finally, consistent with expectations, higher conscientiousness was associated with a greater likelihood of membership in the conventional-dominant profile relative to the investigative profile, which also aligns with variable-centered evidence showing consistent positive associations of conscientiousness with conventional interests (Barrick et al., 2003; Larson et al., 2002). The dispostional organization and orderliness reflected in conscientiousness may be expressed as preferences for routine activities in structured work environments. Taken together, the results converge with prior work showing that levels of personality traits differ as a function of interests profiles. The current results also extend this work by showing predictive relations of personality with interest profile membership, suggesting that personality traits can reliably differentiate among the interest profiles, which is more consistent with theoretical models of interest development positing dispositions as antecedents of interests (Lent et al., 1994; Schuab & Tokar, 2005).

The results have implications for practice. Support for the interest profiles, based on all six interests, may better allow career counselors to provide a more holistic interpretation of clients' interest configurations (Leuty et al., 2016). Indeed, it may be the case that a dynamic interplay among all six interests, rather than one, two, or even the three highest interests, moves individuals towards and away from certain activities and environments (Larson et al., 2014). With information gleaned from all six interests, co-existing at different levels within individuals, practitioners may be better able to design career planning and exploration interventions based on all available information. Specifically, practitioners may use information about individuals' most likely latent class membership to identify vocational opportunities that are best aligned with interest configurations. Indeed, tailoring interventions at the level of latent subgroups is likely to be more economically sustainable, particularly when offered at a large-scale (e.g., whole school career interventions), than individualized interventions, but much more precise than one-size-fits-all interventions that assume that students are homogenous with respect to their interests.

The results also underpin the use of vocational interest data for informing education and career decision-making as manifested in widely-used computerized databases, such as the Occupational Information Network (O*NET) and College Major Finder, commonly used for individual career exploration activities. In the O*NET database, for instance, vocational interest profiles typically implicated in STEM disciplines include a combination of C-R-I (Bruch & Krieshok, 1981). Civil engineers, for example, prototypically present a code of RIC (National Center for O*NET Development, 2016a) whereas mechanical engineers present IRC (National Center for O*NET Development, 2016b). Information analysts present a code of CIR, and biostatisticians present ICR. However, computerized databases are usually limited to three-letter Holland codes, reflecting an individual's three highest interests. Although the three-letter codes implicitly account for interactions among the three highest interests characterizing an individual's vocational profile, this operationalization does not account for the possibility that lower levels of interests may also inform the selection of certain educational and work activities and environments (Elsworth et al., 1999; Larson et al., 2014; Low & Rounds, 2007). As interests are expected to co-manifest at different levels within individuals, a combination of all six interests may inform educational and career choices, including configurations of both high and low interest levels. Thus, the present interest configurations provide an extension of three-letter codes by considering all available individual information.

A few limitations to this research merit attention. First, we note that the small STEM subsample in the present study may have made it difficult to detect some relations of the choice outcomes with profile membership. The small STEM subsample also precluded examination of the relations of profile membership with specific STEM pathways (e.g., science vs. engineering). A further limitation concerns the generalizability of the present results. The findings obtained in this research were based on a single institution serving a large "non-school-leaver" student population. Although Australia has one of the highest rates of non-school-leaver participation in higher education among OECD nations (Coelli & Tabasso, 2015), the large proportion of non-school leavers in the present sample may be considered somewhat unrepresentative of the "traditional" university student population in Australia and abroad. Thus, there is the possibility that some of the findings of the present study are idiosyncratic to our particular sample and do not generalize to more traditional university samples.

Generalizability of the findings remains a key concern for this work. Although findings support the configural, structural, dispersion, and distributional similarity of the interest profiles, which is particularly important in person-centered analyses, where the presence of spurious profiles is difficult to discount, profile replicability was based on random subsamples of the general sample, which should not be expected to show any differences. A more robust approach to examining validity of the interest profiles would be investigating the extent to which the interest configurations generalize across more theoretically-informative demographic characteristics and cultural, educational, and professional contexts. For instance, different gender socialization experiences for males and females (Eccles, 1984) may lead to gender differences in mean levels and variability of the interests (Betsworth & Fouad, 1997; Su, Rounds, & Armstrong, 2009) and, by implication, differences in profile structure and dispersion. There is also evidence for differences in the levels, variability, and structure of the RIASEC dimensions across cultures and countries (Fouad, Harmon, & Hansen, 1994; Rounds & Tracey, 1996). There may be differences in the within-profile variability of the indicators across cultural groups, such that there is more variability in the interest dimensions in cultures where there is more scope for career exploration, fewer perceptions of career barriers, greater autonomy in career decision-making, and less pressure to adhere to cultural norms (Fouad & Byars-Winston, 2005; Gelfand, mishii, & Raver, 2006; Mau, 2000). Also, there may be important gender × cultural group interactions in profile structure, dispersion, and distribution. In addition, it may be that there are distributional differences in profiles across occupational groups, such that in, for example, elementary school students, there might be a higher proportion of ambivalent individuals due to limited career exploration whereas in professional samples, the proportion of ambivalent individuals may be lower due to a clearer vocational roles and identities (Todt & Schreiber, 1998). Differences in structure, dispersion, and distribution may also be found across distinct work environments.

A related issue is the longitudinal stability of the interest profiles. Two forms of longitudinal stability are pertinent. First, the within-sample stability of the profiles is concerned with the extent to which the profile configurations, as well as within-profiles mean, variability, and relative size, are stable across time. For instance, as interests begin to crystalize around adolescence, the relative size of the ambivalent profile may decrease. A second stability type is within-person stability, which concerns the extent of consistency in individuals' profiles over time (Morin, 2016). Although research shows continuity in interest over time in terms of both rank-order and within-person stability (Low, Yoon, Roberts, & Rounds, 2005), this does not preclude the possibility that individuals may transition between profiles, assuming their within-sample stability, across time. What is clear is that more work needs to be done to better understand how generalizable and stable these interest profiles are across contexts and time, respectively.

A final set of limitations concerns the predictors and outcomes of interest profile membership. Although we conceptualized personality as a predictor in line with contemporary theories of choice behaviors, data were cross-sectional, thereby precluding causality or even directionality inferences. Future research would do well to examine the longitudinal relations of personality with changes in interest profile membership beyond basal interest configurations, which would provide more robust support for personality as antecedent of the development of interest configurations. Finally, we restricted the outcome to a binary variable (i.e., STEM vs. Non-STEM). Although this restriction ensured sufficient observations in each criterion cell across the interest profiles, it is plausible that different interest configurations may be more or less implicated in different STEM disciplines and sub-disciplines. Future research would do well to examine a more diverse set of educational and career choices as a function of interest profile membership. Furthermore, though a primary focus of the investigation is on predicting STEM major choices from the interest profiles, the issue of STEM major selection is complex and involves multiple processes and variables. Indeed, from the SCCT perspective on the career choice process, STEM career choices may be expected for those who (a) intend to pursue STEM pathways, (b) are interested in STEM domains, (c) expect favorable outcomes from engaging with STEM-tasks, (d) are efficacious about STEM-related activities, and (e) possess background characteristics and contextual affordances that serve as facilitators or barriers (Lent et al., 1994). Future research would do well to incorporate the profiles obtained in the present study into integrative process model to obtain a more complete understanding of how profiles of interest may serve as the intermediary mechanism through which STEM-related self-efficacy beliefs and outcome expectations are linked with STEM intentions and choice behaviors.

The current study examined latent profiles of vocational interests. Six interest profiles were identified across independent subsamples, including social-dominant, disinterested, high realistic-dominant, investigative-dominant, ambivalent, and conventional-dominant profiles. Notably, the profiles were found to replicate across subsamples under formal tests of profile replicability. Analyses also revealed theoretically-consistent relations of profile membership with the probability of choosing a STEM major, and relations of core personality traits with interest profile membership. From a theoretical standpoint, the current research extends vocational interest theory by integrating normative circular and noncircular representations of interest structure under a common multidimensional, person-centered framework. From an applied perspective, findings of theoretically defensible profiles, which are meaningfully related to educational choices, underpins the use of vocational interest data to inform educational and vocational decision-making, extending Holland three-letter codes by considering all available interest information on individuals.

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Table 1. Means, Standard Deviations, and Correlations for the RIASEC factor score mixture indicators and Big-Five variables.

Variable	M_1 (SD)	M_2 (SD)	1	2	3	4	5	6	7	8	9	10	11
1. Realistic	0.015 (.884)	0.001 (.961)	–	.482	.421	.225	.493	.619	.011	-.099	-.086	-.098	.009
2. Investigative	0.011 (.933)	-0.026 (.944)	.474	–	.446	.362	.187	.309	.042	.103	.000	-.070	.037
3. Artistic	-0.012 (.937)	-0.002 (.903)	.399	.507	–	.542	.495	.261	.146	.202	-.103	.046	.295
4. Social	-0.034 (.940)	-0.013 (.890)	.118	.384	.546	–	.574	.394	.224	.450	-.038	.109	-.056
5. Enterprising	-0.004 (.897)	-0.005 (.920)	.411	.261	.496	.515	–	.647	.229	.200	-.025	.069	-.022
6. Conventional	0.030 (.954)	-0.033 (.941)	.565	.213	.158	.225	.621	–	-.002	.040	.066	.129	-.141
7. Extraversion	2.976 (.907)	3.075 (.941)	-.085	.063	.098	.288	.131	-.055	–	.308	.083	-.171	.203
8. Agreeable	3.946 (.804)	3.985 (.732)	-.224	.082	.163	.429	.069	-.079	.219	–	.122	.036	.142
9. Conscientious	3.722 (.777)	3.769 (.734)	-.078	-.065	-.229	-.054	-.037	.111	-.020	.049	–	-.091	.013
10. Neuroticism	2.918 (.855)	2.834 (.785)	.011	.005	.116	.087	.091	.047	-.091	.009	-.119	–	-.048
11. Openness	3.805 (.776)	3.771 (.747)	.105	.211	.284	.071	-.070	.071	.071	.150	-.008	-.051	–

Note. M_1 = means (and standard deviations) for subsample 1; M_2 = means and standard deviations for subsample 2. Correlations below the diagonal are for subsample 1, and correlations above the diagonal are for subsample 2.

Table 2. Fit indices and classification accuracy for the single-sample and multiple-group latent profile models.

Class Enumeration: Subsample 1	k	LL	#fp	AIC	BIC	SaBIC	CAIC	Entropy	BLRT
One profile	1	-3068.107	12	6160.213	6207.558	6169.484	6219.559	–	–
Two Profiles	2	-2857.729	19	5753.457	5828.420	5768.136	5847.421	.868	< .001
Three Profiles	3	-2779.855	26	5611.711	5714.291	5631.798	5740.291	.828	< .001
Four Profiles	4	-2726.886	33	5519.772	5649.971	5545.267	5682.971	.840	< .001
Five Profiles	5	-2697.792	40	5475.583	5633.400	5506.487	5673.400	.763	< .001
Six Profiles	6	-2672.828	47	5439.656	5625.091	5475.968	5672.091	.764	< .001
Seven Profiles	7	-2651.625	54	5411.249	5624.302	5452.969	5678.303	.757	< .001
Eight Profiles	8	-2631.210	61	5384.421	5625.091	5431.548	5686.091	.779	< .001
Nine Profiles	9	-2615.083	68	5366.166	5634.455	5418.702	5702.455	.796	< .001
Class Enumeration: Subsample 2									
One profile	1	-3073.553	12	6171.105	6218.450	6180.376	6230.451	–	–
Two Profiles	2	-2869.053	19	5776.106	5851.069	5790.785	5870.069	.802	< .001
Three Profiles	3	-2767.338	26	5586.676	5689.257	5606.763	5715.257	.871	< .001
Four Profiles	4	-2728.668	33	5523.336	5653.534	5548.831	5686.535	.779	< .001
Five Profiles	5	-2687.506	40	5455.012	5612.829	5485.915	5652.829	.776	< .001
Six Profiles	6	-2657.554	47	5409.108	5594.543	5445.420	5641.543	.780	< .001
Seven Profiles	7	-2632.906	54	5373.812	5586.865	5415.532	5640.865	.803	< .001
Eight Profiles	8	-2610.076	61	5342.152	5582.823	5389.280	5643.823	.809	< .001
Nine Profiles	9	-2591.526	68	5319.052	5587.340	5371.588	5644.977	.803	< .001
Multiple-group similarity									
Configural	6	-5859.947	95	11909.893	12350.557	12048.890	12445.668	.836	–
Structural (eq. means)	6	-5892.935	59	11903.870	12177.546	11990.195	12236.546	.831	–

Dispersion (eq. means + variances)	6	-5894.852	53	11895.704	12141.548	11973.250	12194.548	.830	–
Distributional (eq. means + variances + probabilities)	6	-5898.005	48	11892.010	12114.661	11962.240	12162.661	.828	–

Note. *k* = number of profiles; LL = model log-likelihood; #fp = number of free parameters; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion; SaBIC = sample-size-adjusted Bayesian Information Criterion; CAIC = Consistent Akaike Information Criterion; BLRT = Bootstrap Likelihood Ratio Test.

Table 3. Equality Tests of STEM Major Choice Probabilities Across the Six Profiles

Outcome	Profile 1: Weak-Social Dominant (a)	Profile 2: Disinterested (b)	Profile 3: High Realistic-Dominant (c)	Profile 4: Investigative-Dominant (d)	Profile 5: Ambivalent (e)	Profile 6: Conventional-Dominant (f)	Omnibus Test
Stem Major Choice	$.017_{cdef}$	$.072_{cf}$	$.240_{abf}$	$.183_{af}$	$.184_{af}$	$.590_{abcde}$	69.218

Note. N = 715. Subscripts denotes profiles that differ significantly at $p < .05$. The omnibus test of significance is a chi-square test with df = 5.

Table 4. Results from the Multinomial Logistic Regression Models of the Effects of the Big-Five Personality Dimensions on Latent Profile Membership using the Auxiliary Three-Step Procedure.

	1 Vs 6		2 Vs 6		3 Vs 6		4 Vs 6		5 Vs 6		1 Vs 5		2 Vs 5	
	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR
Ext	0.553*	1.738	0.395	1.484	0.327	1.387	0.141	1.151	0.889**	2.433	-0.335	0.715	-0.494*	0.610
	(0.279)		(0.256)		(0.227)		(0.268)		(0.281)		(0.224)		(0.225)	
Agree	1.518***	4.563	0.381	1.464	0.699*	2.012	0.870**	2.387	1.075**	2.93	0.443	1.557	-0.694*	0.499
	(0.331)		(0.276)		(0.220)		(0.266)		(0.329)		(0.349)		(0.319)	
Consc	-0.409	0.664	-0.167	0.846	-0.556	0.573	-0.749*	0.473	-0.414	0.661	0.005	1.005	0.248	1.281
	(0.335)		(0.337)		(0.293)		(0.337)		(0.354)		(0.254)		(0.294)	
Neurot	0.294	1.342	-0.056	0.946	0.155	1.168	0.127	1.135	0.363	1.438	-0.069	0.933	-0.419	0.658
	(0.315)		(0.317)		(0.271)		(0.321)		(0.322)		(0.224)		(0.253)	
Open	0.178	1.195	0.606*	1.833	0.525*	1.690	1.082**	2.951	0.548	1.729	-0.369	0.691	0.058	1.059
	(0.283)		(0.304)		(0.226)		(0.325)		(0.321)		(0.265)		(0.311)	

	3 Vs 5		4 Vs 5		1 Vs 4		2 Vs 4		3 Vs 4		1 Vs 3		2 Vs 3	
	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR
Ext	-0.561**	0.571	-0.747**	0.474	0.412	1.510	0.253	1.288	0.186	1.204	0.226	1.254	0.068	1.070
	(0.201)		(0.232)		(0.239)		(0.205)		(0.177)		(0.187)		(0.157)	
Agree	-0.376	0.687	-0.205	0.815	0.649*	1.914	-0.488	0.614	-0.170	0.844	0.819**	2.268	-0.318	0.728

	(0.288)		(0.312)		(0.322)		(0.258)		(0.200)		(0.275)		(0.204)	
Consc	-0.141	0.868	-0.335	0.715	0.340	1.405	0.583*	1.791	0.194	1.214	0.146	1.157	0.389	1.476
	(0.244)		(0.268)		(0.246)		(0.274)		(0.198)		(0.201)		(0.217)	
Neurot	-0.208	0.812	-0.236	0.790	0.167	1.182	-0.183	0.833	0.028	1.028	0.139	1.149	-0.211	0.808
	(0.210)		(0.248)		(0.239)		(0.468)		(0.196)		(0.179)		(0.189)	
Open	-0.023	0.977	0.535	1.707	-	0.405	-0.476	0.621	-0.558*	0.573	-0.346	0.706	0.081	1.084
	(0.259)		(0.331)		0.904**		(0.324)		(0.261)		(0.193)		(0.223)	
					(0.318)									

	1 Vs 2	
	Coef. (SE)	OR
Ext	0.158	1.171
	(0.213)	
Agree	1.137***	3.117
	(0.316)	
Consc	-0.243	0.784
	(0.262)	
Neurot	0.349	1.418
	(0.229)	
Open	-0.428	0.652
	(0.269)	

Note. Ext = Extraversion; Agree = Agreeableness; Consc = Conscientiousness; Neurot = Neuroticism; Open = Openness to Experience. SE = standard error; OR = Odds Ratio; *** $p < .001$, ** $p < .01$, * $p < .05$

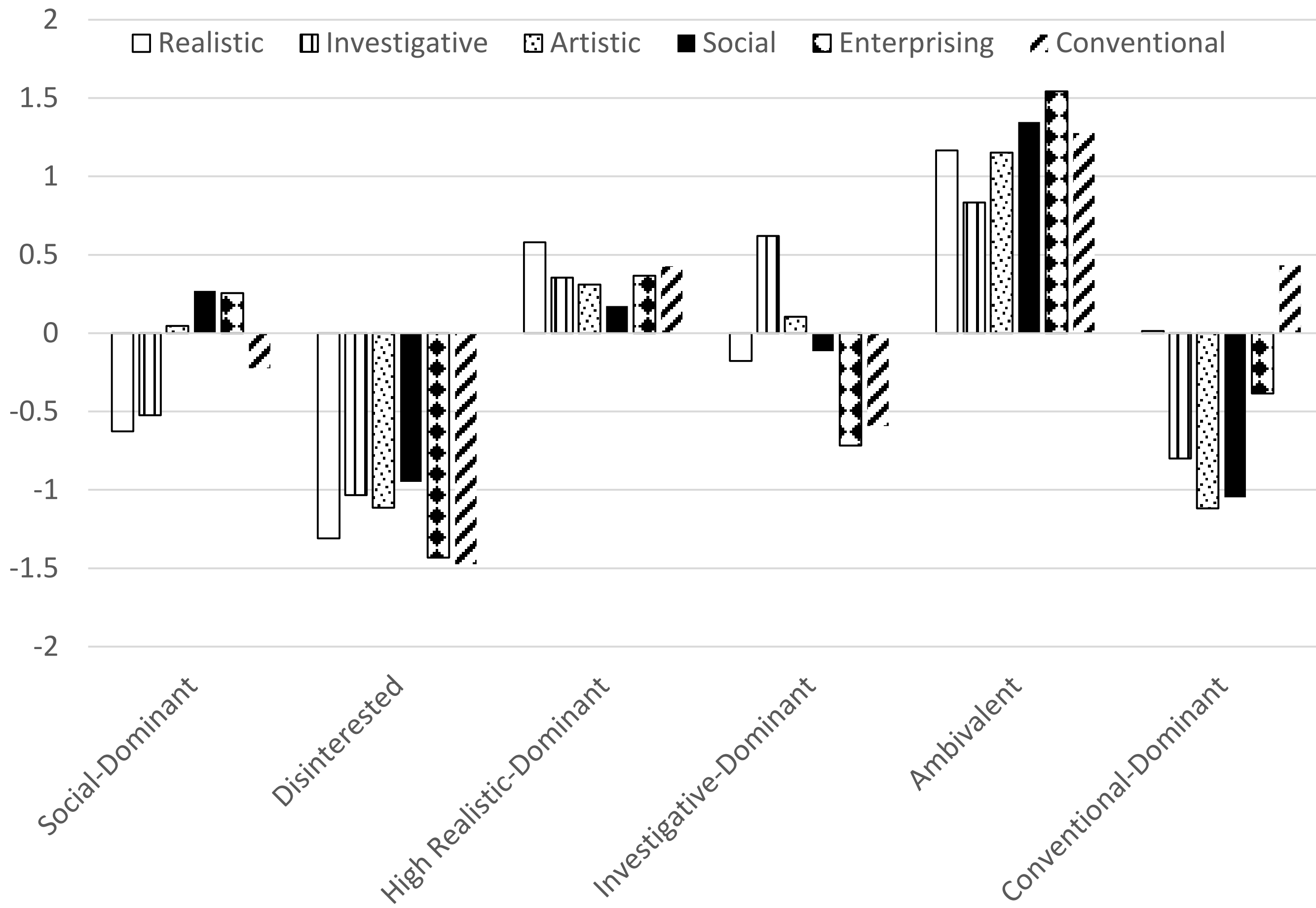

Figure 1. Mean vocational interest factor scores for each of the six identified interest profiles.

Highlights

- Latent profiles of vocational interests were identified.
- The profiles replicated across subsamples.
- Big-Five personality dimensions differentiated the profiles.
- Profile membership was associated with the probability of STEM major choice.