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The Relations of Vocational Interests and Mathematical Literacy

On the Predictive Power of Interest Profiles

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This study examines the relationships of vocational interests and mathematical literacy both cross-sectionally and longitudinally. Extending previous research, the results of Holland's RIASEC (Realistic, Investigative, Artistic, Social, Enterprising, and Conventional) scale scores are compared with results from a reductionist approach using individual interest profiles (including the parameters level, differentiation, and orientation). Both analyses find significant relations between interests and mathematical literacy. The scale score analyses reveal positive associations of Realistic interests with mathematical literacy, whereas Artistic interests show a negative association. Interest profiles from a dimensional representation show individuals with interest orientations close to the Realistic domain score highest on mathematical literacy, with those with interests in both Artistic and Social domains scoring lowest. Results from profile analyses suggest that interest differentiation moderates the interest–ability relation. Only interest profiles are predictive for mathematical literacy over and above covariates, indicating that interest profiles are more robust predictors than the scale scores. Analyses show that interest profiles are a valid reduction of the scale score models.

Keywords: *vocational interests; interest profiles; mathematical literacy; interest orientation; interest level; interest differentiation; longitudinal study*

Vocational interests develop in adolescence (Tracey, 2001) and become increasingly stable over time (Low, Yoon, Roberts, & Rounds, 2005). Holland (1959, 1997) proposed a model that characterizes vocational interests in terms of six orientations: Realistic,

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Investigative, Artistic, Social, Enterprising, and Conventional. Individuals can be classified to their dominant interest orientation (i.e., as a type belonging to any one of these six orientations) based on their responses to an interest inventory. According to Holland's RIASEC (Realistic, Investigative, Artistic, Social, Enterprising, and Conventional) model, these interest orientations are associated with different values, attitudes, and abilities. For example, people with strong interests in the Artistic domain are expected to shine in languages and the arts, whereas people with strong interests in the Investigative and Realistic domains are expected to show high abilities in mathematics. Holland has suggested that these interest–ability relations develop as a result of the interaction of genetic and environmental factors. Ackerman's (1996) Process, Personality, Interests, and Knowledge Theory of Intellectual Development (PPIK) provides a theoretical framework that specifies the mechanisms underlying the postulated relationships. According to his theory, interests and abilities develop in a reciprocal relationship. Domain-specific interest prompts people to engage more intensely with the object of interest, leading to an increase in the corresponding skills and abilities. Should they lack the necessary skills and abilities, however, repeated experiences of failure will lead to a decrease in interest.

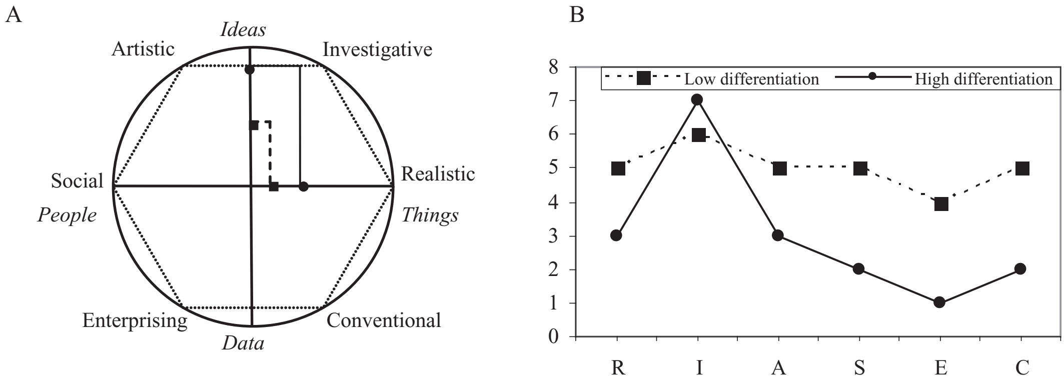
Several empirical studies have investigated the associations between Holland's vocational interest types and domain-specific abilities. Many findings were synthesized in the meta-analysis by Ackerman and Heggestad (1997). The authors found consistent positive relations between, for example, interests in the Realistic or Investigative domains and mathematical abilities, and interests in the Investigative or Artistic domains and verbal abilities. A more recent study investigated time-lagged relations between RIASEC scores and academic abilities in the domains of mathematics and English (Tracey, Robbins, & Hofsess, 2005). Contrary to expectations, however, no time-lagged relations were found between vocational interests and academic skills.

Strong (1955) pointed out that the correlations of interest and ability test scores may not measure the true association between interests and abilities and that the data are too complex to be adequately described by the methodologies previously used (c.f., Randahl, 1991). Therefore, instead of focusing on the relationship between single interest and ability *measures*, other authors have examined the relationship between interest and ability *profiles*. Randahl (1991) presented evidence to show that different interest profiles are associated with distinct ability profiles. In a more recent study, Reeve and Hakel (2000) identified significant intraindividual correlations that increased with the age of the respondents (see also Denissen, Zarret, & Eccles, 2007). Although these studies provide evidence for associations between interest profiles and abilities, they do not consider the systematic pattern of RIASEC profiles proposed in Holland's theory.

RIASEC Structure and RIASEC Profiles

According to Holland (1997), individuals differ in their interest profiles, but all profiles are organized according to the same principles. In his hexagonal model, the six interests are represented in a two-dimensional space, with psychological similarity between the orientations determining their relative position and proximity on the hexagon: Interest domains are

Figure 1
Interest Profiles Based on Holland's RIASEC Model



Note. Representation of interest profiles (A) based on Prediger's (1982) things/people and data/ideas dimensions and (B) as a scale score model. R = Realistic; I = Investigative; A = Artistic; S = Social; E = Enterprising; and C = Conventional.

located next to those to which they are most similar and opposite those to which they are most dissimilar. The scale scores thus show a specific pattern of correlations: The relationships of adjacent types (e.g., R–I) should be higher than between alternating types (e.g., R–A), which in turn should be higher than those of opposite types (e.g., R–S). There is strong empirical support for this hexagonal structure (see Nagy, Trautwein, & Lüdtke, IN PRESS; Rounds & Tracey, 1993; Tracey & Rounds, 1993). Figure 1A provides a graphical representation of Holland's structural model.

Holland proposed three characteristics of individual RIASEC profiles: consistency, orientation, and differentiation. First, consistency refers to the placement agreement of individual's highest interest domains. Holland uses the two highest scale scores to define three degrees of consistency: Adjacent orientations (e.g., R–I) are most consistent, alternating orientations (e.g., R–A) have an intermediate level of consistency, and opposite types (e.g., R–S) are least consistent. Second, a RIASEC profile can be characterized by an individual's interest orientation. Interest orientation is probably the most salient feature of an individual profile. It refers to an individual's dominant or highest interest domain. Figure 1B gives an example of a hypothetical RIASEC profile with an interest orientation in the Investigative domain. Finally, interest *differentiation* indicates the extent to which a person's dominant interests stand out from her or his other interests. In a highly differentiated interest profile, individual preferences are easily identified. In less differentiated profiles, preferences become more difficult to identify. Holland expected differentiation to function as a moderator, particularly of the association between outcome and person–environment congruence, with stronger relationships being expected for people with differentiated profiles than for those with undifferentiated profiles. Figure 1B illustrates two consistent individual scale score profiles, both with a dominant Investigative orientation, but one with low and the other with high interest differentiation.

Structural Summary of Individual RIASEC Profiles

According to Prediger's (1982) dimensional model, the spatial RIASEC structure can be represented by a three-factor solution. Factor analyses typically reveal a prominent general factor with comparably high loadings on all six scales (see Rounds & Tracey, 1993; Tracey & Rounds, 1993). The structural aspect of Holland's model is reflected in two additional basic dimensions: things/people (horizontal axis in Figure 1A) and data/ideas (vertical axis in Figure 1A). Plotting the loadings of the things/people and data/ideas factors typically produces the graphical representation given in Figure 1A (Tracey, 2000).

As outlined by Nagy et al. (IN PRESS; see also Tracey & Robbins, 2005, 2006), Prediger's (1982) factors capture the most fundamental aspects of individuals' RIASEC profiles. The general factor reflects interindividual differences in the overall level of interests (i.e., the mean interest defined over all RIASEC domains). It has been given a number of labels, including "acquiescent style" (Holland, 1985, p. 5), "response style" (Prediger, 1998, p. 205), or "general interest factor" (Darcy & Tracey, 2003, p. 228).

Individuals' scores on the things/people and data/ideas dimensions provide information about their interest orientation and interest differentiation (Nagy et al., IN PRESS). As shown by Nagy and colleagues, the things/people and data/ideas factor scores can be regarded as a multiplicative function of individuals' interest differentiation and the sine or cosine of their interest orientation. This relation is visualized in Figure 1A, which plots the scores of two hypothetical persons on Prediger's factors. Both persons are located in the Investigative corner of the hexagon. However, they differ in their interest differentiation: One is located close to the origin of the things/people and data/ideas coordinate system (i.e., low differentiation), whereas the other is located close to the edge of the coordinate system (i.e., high differentiation). For more details, see Nagy et al. (IN PRESS).

Taken together, the three dimensions proposed by Prediger (1982) provide a reductionist representation of RIASEC profiles according to the principles proposed by Holland (1997). Dimensional scores thus provide a structural summary (Gurtman & Balakrishnan, 1998) of individuals' interest profiles. As a consequence, interest profiles can be related to external variables, such as mathematical literacy, making it possible to evaluate the predictive power of each individual profile parameter. To our knowledge, however, research taking such an approach is currently scarce.

Prediger (1998) examined the role of interest level in predicting occupational choices but found interest level to be unrelated to behavior. However, in a theoretical article, Darcy and Tracey (2003) interpreted the general interest factor as an indicator of interest flexibility and expected it to show moderate positive relationships to outcome measures, such as achievement, satisfaction, and stability. Moreover, they hypothesized interest flexibility to be a moderator of the relations between person–environment congruence and outcome measures, postulating that individuals with a high profile level would exhibit a lower correlation between person–environment congruence and outcome measures than individuals with a low profile level. Tracey and Robbins (2006) confirmed this moderation hypothesis using the overall profile level, calculated as the mean score across all six RIASEC scales. However, they did not find profile level to be directly associated with college success or persistence.

Recently, Nagy (2006) related individual's profile orientation and interest differentiation—as reflected in the things/people and data/ideas factors—to abilities in the mathematical and verbal domains and found the theoretically predicted correlations. Analyses showed that the closer an individual's interest orientation was to the Realistic and Investigative domains, the higher his or her mathematics achievement. Verbal abilities, in turn, were highest for individuals with dominant interests in the Artistic and Social domains.

Research Questions

This study investigates the associations between vocational interests and mathematical literacy from both a cross-sectional and a longitudinal perspective. In so doing, it follows up on the few studies to date that have examined the associations between profiles of vocational interests and abilities (e.g., Nagy, 2006; Randahl, 1991; Tracey & Robbins, 2006). Although the six scale score models use information from all RIASEC variables, the underlying dimensional arrangement means that the scale scores show a specific pattern of correlations and thus include redundant information. Interest profiles based on a structural summary (Gurtman & Balakrishnan, 1998) allow vocational interests to be described more parsimoniously. This method seems particularly attractive and valuable because it further allows aspects of interest orientations that predict a person's abilities positively or negatively to be identified. The validity of this reductionist method remains to be confirmed, however.

To examine the robustness of the associations between interest profiles and mathematical literacy, we controlled for relevant covariates. Previous research has shown consistent gender differences in both mathematical abilities and vocational interests. A large body of research with young adults has shown that males outperform females in mathematics, especially in mathematical problem-solving tasks (Geary, 1996; Hosenfeld, Köller, & Baumert, 1999). At the same time, previous studies on vocational interests have repeatedly found gender differences in interest orientations. As a rule, men show more interest in the Realistic domain, and women more interest in the Social domain (Lippa, 1998; R. L. Mullis, Mullis, & Gerwels, 1998; Nagy, 2006; Nagy et al., IN PRESS; Tracey & Ward, 1998). In our longitudinal analyses, moreover, we controlled for prior knowledge, which is known to be a strong predictor of future knowledge (Alexander & Judy, 1988; Dochy, 1992).

Specifically, we expected to find the following patterns of results:

We expected the scale score models to show positive associations between interests in the Realistic and Investigative domains and mathematical literacy both cross-sectionally and longitudinally. Furthermore, due to the specific structure of Holland's RIASEC model, we expected to find negative associations between Artistic and Social interests and mathematical literacy.

We expected interest profiles to be associated with mathematical literacy in the cross-sectional and the longitudinal analyses. It was not possible to draw on an existing body of findings to formulate specific predictions for interest level. However, we expected to find higher mathematical literacy at both points of measurement with increasing proximity of individual's dimensionally represented orientation to the Realistic and Investigative domains. We also assumed differentiation to be an important profile parameter that moderates the interest–ability relation. We, therefore, expected models in which profile orientation was weighted by differentiation to provide better predictions of mathematical literacy than models including unweighted profile orientation.

A main focus of our study was to examine the validity of the reductionist interest profile method. This method provides a valuable tool in career counseling and assessment because it allows aspects of interest orientations that predict a person's mathematical literacy positively or negatively to be specified. We expected the predictive power of interest profiles to be comparable to that of the scale score models. In other words, we expected the reduction to summarize the most relevant interest information.

To examine the robustness of the results, we analyzed whether there was still a positive association of vocational interests and mathematical literacy when gender and prior abilities in mathematical literacy were controlled. We further investigated the incremental effect of vocational interests beyond these covariates.

Method

Sample and Procedures

All participants were 11th graders from a German academic-track school specializing in economics. The students were administered a mathematics test in the middle and at the end of Grade 11, at an interval of approximately 6 months. Students also completed a questionnaire tapping their vocational interests. The sample comprised 168 students at the first point of measurement (T1) and 128 students at the second point of measurement (T2). The decrease in participants was caused by illness, students dropping out of school or moving to new schools, and refusal to participate at T2. Participants' average age at T1 was 18.15 years ($SD = 1.49$); 46% of participants were female.

Missing data caused by systematic dropout limit the generalizability of longitudinal findings (Allison, 2002).Thus, a variety of algorithms have been proposed for dealing with missing data (c.f., Collins, Schafer, & Kam, 2001). There is growing consensus that the expectation-maximization algorithm and multiple imputation produce less biased estimates than do pairwise or listwise deletion. Therefore, we used multiple imputation methods to estimate missing values in the current study. The NORM 2.03 software (Schafer, 1999) was used to generate 20 data sets and Rubin's rules were applied to combine estimates and standard errors (c.f., Rubin, 1987; Schafer & Graham, 2002).

Instruments

Mathematical literacy was assessed using the mathematical literacy test developed and administered in the Third International Mathematics and Science Study (TIMSS; I. V. S. Mullis et al., 1998). In line with the literacy debate (National Council of Teachers of Mathematics, 1989), the mathematical content covered in the test items is embedded in everyday contexts. Although the literacy concept does not require curricular validity in the strict sense, validity studies have confirmed the TIMSS items' validity with respect to both the curriculum and the learning opportunities afforded in the classroom (Klieme, Baumert, Köller, & Bos, 2000). The mathematical literacy test is based on item response theory; the item parameters derived from TIMSS were used to scale the test scores. We used the Conquest software (Wu, Adams, & Wilson, 1998) to calculate weighted likelihood estimates (WLE, Warm, 1989) as person parameters for each student. The items used at both occasions were characterized by TIMSS experts as especially relevant for defining mathematical literacy and covered a broad range of item difficulty. This procedure resulted in a broad achievement test with good content validity. However, levels of internal consistency were lower than in more narrowly defined achievement tests. The reliabilities of the WLE scores were estimated by dividing the measures of "true" variance (variance of the mathematics factor) by the variance of the WLE scores (see Rost, 2004, Formula 6, p. 381). Reliability was $r = .65$ at T1 and $r = .50$ at T2.

The scores were standardized at $M = 0$ and $SD = 1$ at T1. Using this mean and standard deviation, the scores were transformed at T2 ($M = -0.21$, $SD = 1.42$). Mean abilities in mathematical literacy were thus found to decrease somewhat, but the difference was not statistically significant ($z = 1.73$, $p = .083$). The test scores showed a rank order stability of $r_{tt} = .56$ ($p < .01$).

Vocational interests were assessed by means of the revised general interest structure test (GIST; Allgemeiner Interessen Strukturtest; Bergmann & Eder, 2005), an established German instrument based on Holland's model. The GIST is the best validated interest inventory in the German-speaking countries (i.e., Germany, Austria, and Switzerland). Scale score correlations between the GIST and an adaptation of Holland's Self-Directed Search instrument (Jörin, Stoll, Bergmann, & Eder, 2004) range from $r = .60$ to $r = .75$. Nagy et al. (IN PRESS) recently presented evidence for the structural validity of the GIST, showing that the inventory produces the same rough hexagonal structure as other RIASEC measures. The 1-month retest reliability ranges from $r = .85$ to $r = .92$ (Bergmann & Eder, 2005). The test comprises 60 items, 10 for each of the 6 interest dimensions. Each item describes a school-related or occupational activity. Respondents are asked to state how interested they are or would be in a specific activity on a 5-point Likert scale (1 = *not at all* to 5 = *very*). The internal consistencies (Cronbach's α) of the six scales in the present sample were $\alpha = .77$ or higher. The sample-specific means of the RIASEC scales were standardized against normative data secured from $N = 2{,}716$ students at traditional academic-track Gymnasium schools (Köller, Watermann, Trautwein, & Lüdtke, 2004).

Derived Variables

Vocational interests according to Holland's RIASEC model were calculated in two ways: one using the six scale scores and the other based on interest profiles as comprised in a structural summary (Gurtman & Balakrishnan, 1998). Profile level was calculated by computing the mean of the six scale scores. Profile orientation and differentiation were derived from things/people and data/ideas dimensional scores (c.f., Prediger, 1982; Prediger & Vansickle, 1992). To this end, we first transferred the standardized scale scores to a coordinate system described by Prediger's (1982) things/people (cosine) and data/ideas (sine) axes. We assumed a regular hexagon, with the six interest scales being uniformly distributed around a circle. Each of the six RIASEC variables was given a fixed angular location (Realistic = 0°, Investigative = 60°, Artistic = 120°, and so on). To calculate the dimensional scores, we multiplied the six standardized scale scores by the cosine of the corresponding variable's angular position and then summed them to a (weighted) cosine score (i.e., things/people). The (weighted) sine score (i.e., data/ideas) was calculated in the same way but using the sine of the corresponding variable's position. For instance, positive scores on the things/people (cosine) and data/ideas (sine) dimensions represent an Investigative orientation, whereas negative scores on these dimensions relate to a Conventional orientation (see Figure 1A). Both dimensional scores include information about profile orientation *and* differentiation.

As outlined by Nagy et al. (IN PRESS), an individual's (i) things/people score can be denoted as $\alpha_i \times \cos(\delta_i)$ and his or her data/ideas score as $\alpha_i \times \sin(\delta_i)$, where α_i denotes the interest differentiation and δ_i the interest orientation. Note that δ is an angular measure (ranging from 0° to 360°) that indicates the location of a person's dominant interest. The specified relations between dimensional things/people and data/ideas scores make it possible to disentangle profile differentiation from profile orientation. We use this decomposition to examine the moderating role of profile differentiation on the interest–outcome relation.

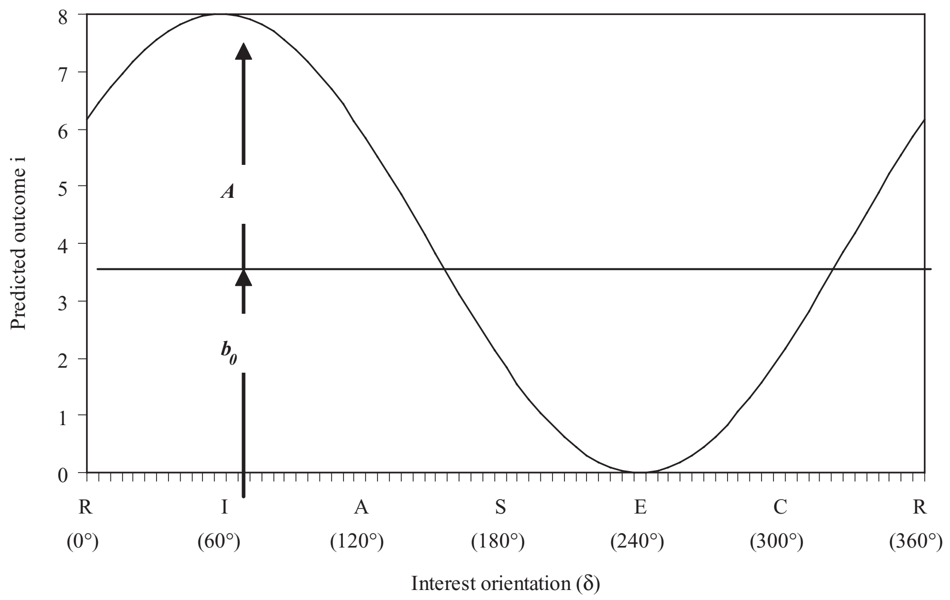
Analysis Strategy

Multiple regression analyses were performed to predict mathematical literacy. We used the six RIASEC variables as predictors of mathematical literacy in regression models with scale scores. In the reductionist interest profile method, the predictor variables were interest level and the things/people and data/ideas scores (see also Batschelet, 1981). The resulting regression coefficients were b_0 (intercept), b_l (level), b_c (things/people), and b_s (data/ideas). They describe the relation between individual interest profiles and an outcome measure. The first parameter b_0 is a conventional regression intercept. The level effect (b_l) captures change in mathematical literacy as a function of individual's overall interest level. Finally, the parameters b_c and b_s reflect the relationships between individuals' interest orientations and mathematical literacy. Both regression coefficients can be used to define two key parameters. First, the peak θ represents the interest orientation (in degree units) that is most positively associated with a given criterion. It is calculated by taking the arc tangent of the regression coefficient of the data/ideas (b_s) scores divided by the regression coefficient of the things/people (b_c) scores, $\theta = \arctan\left(\frac{b_s}{b_c}\right)$. The parameter θ stands for the interest region in which the highest level of mathematical literacy is expected to occur. Based on previous research, we expect an estimate of θ close to 0°, the angular location of Realistic interests.

Second, the parameter A stands for the effect amplitude. This parameter reflects the difference in the expected outcome measure between individuals with an interest orientation equal to θ (i.e., the peak) and the mean value of the outcome across all possible interest orientations. A is calculated as the root of the sum of the squared coefficients of the things/people (b_c) and data/ideas (b_s) dimensional scores, $A = \sqrt{b_c^2 + b_s^2}$. When an individual's interest orientation δ_i equals the peak, the amplitude has reached its maximum, and the highest outcome value is expected to occur. The amplitude follows a sinusoidal path, decreasing until it reaches its maximal distance—in terms of a two-dimensional representation—from the peak and then increasing again with proximity to the peak.

Figure 2 gives an example of the parameters described above. Note that Figure 2 does not visualize the effect of the interest level (b_l), because this would unduly complicate the diagram (see Appendix for more details on the method used).

Figure 2
Model Parameters in Interest Profiles Based on a Two-Dimensional Representation



Note. The mean outcome value across the entire range of interest orientations is $b_0 = 4$. The peak θ (about 60°, I) reflects the orientation that is most positively associated with the outcome measure. When an individual's interest orientation δ_i equals the peak, the amplitude has reached its maximum with $A = 4$. R = Realistic; I = Investigative; A = Artistic; S = Social; E = Enterprising; and C = Conventional.

To contrast the predictive power of this method with that of the scale score model, we compared the R^2 values exploratively in terms of confidence intervals. We derived nonsymmetrical 95% confidence intervals using the bootstrap methods implemented in Mplus 5.1 (Muthén & Muthén, 2007). Specifically, we computed the 95% intervals for each imputation and then averaged the results over 20 imputations.

Finally, we included additional predictors in our profile analyses to examine the robustness of the associations between interests and mathematical literacy. We used the $\triangle R^2$ statistic to evaluate whether interests contribute to the prediction of mathematical literacy above and beyond the covariates gender and prior abilities. Statistical significance of the derived $\triangle R^2$ was evaluated by estimating regression models including covariates in which the effects of interest were fixed to zero. We converted the derived χ^2 values into F statistics (c.f., Allison, 2002, p. 68). Significant F values indicate nonzero incremental effects of interests beyond the covariates.

Results

Table 1 documents the correlations between the RIASEC scale scores, mathematical literacy at the first (T1) and the second point of measurement (T2), and gender. For the most

Table 1
Means, Standard Deviations, and Correlations Between Interest Scale Scores, Mathematical Literacy (ML) at T1 and T2, and Gender

Variable	1.	2.	3.	4.	5.	6.	7.	8.	*M*	*SD*
1. R									0.21	0.86
2. I	.61**								–0.11	0.82
3. A	.26**	.35**							–0.13	0.96
4. S	.08	.17*	.50**						–0.21	0.86
5. E	.21**	.29**	.26**	.51**					0.18	1.06
6. C	.33**	.36**	.12	.27**	.43**				0.48	0.97
7. ML T1	.18*	.10	–.18*	.12	.01	.02			0.00	1.00
8. ML T2	.17*	.08	–.24**	–.23**	–.07	.03	.58**		0.21	1.42
9. Gender	–.30**	.15*	–.27**	–.33**	.07	–.02	.31**	.28**		

Note. Higher coding number for males. R = Realistic; I = Investigative; A = Artistic; S = Social; E = Enterprising; and C = Conventional.
* $p < .05$. ** $p < .01$.

part, the intercorrelations of the RIASEC scale scores were in line with the pattern typical of the hexagonal structure. Adjacent scales, such as Realistic and Investigative (r = .61) or Realistic and Conventional (r = .33), showed higher correlations than nonadjacent scales, such as Realistic and Artistic (r = .26) or Realistic and Enterprising (r = .21); the lowest correlations were found between opposite scales, such as Realistic and Social (r = .08).

As shown in Table 1, the RIASEC scale scores showed a systematic pattern of correlations with mathematical literacy and with gender. Mathematical literacy correlated positively with a Realistic orientation at T1 (r = .18) and T2 (r = .17) and negatively with Artistic interests at both times (T1: r = –.24, T2: r = –.18). Furthermore, mathematical literacy at T2 was negatively associated with a Social orientation (r = –.23). As expected, the correlations between gender and interest scale scores revealed particularly high interests for men in the Realistic domain (r = .31) and for women in the Social (r = –.33) and Artistic (r = –.27) domains.

The means of the scale scores reflected the school's focus on economics. The students showed higher interests in the Realistic, Conventional, and Economic domains, whereas their interests in Investigative, Artistic, and Social activities were lower than those of students in traditional academic-track schools.

To test for the structural pattern of the RIASEC scale scores, we tested the fit of our measures to the hypothesized RIASEC structure using Tracey's (1997) RANDALL program. This program conducts a randomization test and provides a correspondence index (CI). The randomization test (Hubert & Arabie, 1987) yields a significance level for the number of order predictions met by the data compared against a null conjecture of random ordering. The CI is an interpretative aid and has a numeric range from –1 to +1, with values close to 0 indicating a random fit of the data and a value of +1 indicating a perfect fit. The results revealed a very good fit (p = .0167, CI = .81).

Table 2 reports the correlations of the interest profile parameters derived from dimensional scores with mathematical literacy and with gender. The things/people orientation—unweighted and weighted by differentiation—was positively associated with mathematical

Table 2
Correlations Between Interest Profile Parameters (Level, Unweighted Interest Orientation, and Interest Orientation Weighted by Differentiation), Mathematical Literacy (ML) at T1 and T2, and Gender

	ML T1	ML T2	Gender
Level	.00	–.08	–.03
Things/people unweighted	.18*	.26**	.42**
Data/ideas unweighted	–.00	–.01	–.13†
Things/people weighted	.23**	.32**	.41**
Data/ideas weighted	–.07	–.06	–.11

Note. Higher coding number for males.
† $p < .10$. * $p < .05$. ** $p < .01$.

literacy and with gender at both times. In contrast, neither interest level nor the data/ideas dimension was found to be significantly correlated with the outcome measure.

Relations of Vocational Interests and Mathematical Literacy

The aim of our study was to investigate the associations between vocational interests and mathematical literacy from both a cross-sectional and a longitudinal perspective, drawing on both interest scale scores and interest profiles. Table 3 presents the results of the multiple regression analyses using scale scores. At both times, mathematical literacy was positively related to a Realistic orientation and negatively related to an Artistic orientation. The amount of variance explained was $R^2 = .092$ in the cross-sectional and $R^2 = .137$ in the longitudinal analysis.

Table 3 also includes the covariate models. As shown, gender was related to mathematical literacy at T1. At T2, only prior abilities were significantly associated with mathematical literacy. Regression analyses revealed that only an Artistic orientation showed a weak relation to mathematical literacy when gender was controlled, with a R^2 of .128 for this model. In the longitudinal analysis controlling for gender and prior abilities, no association of interest scale scores and mathematical literacy could be confirmed. The amount of variance explained by this model was $R^2 = .384$. As indicated by the $\triangle R^2$ statistics in Table 3, the scale scores contributed only weakly to mathematical literacy above and beyond the covariates.

The simple variant of the interest profile model considered interest level and unweighted profile orientation (see Appendix, Equation 1) as predictors of mathematical literacy. Interest level did not significantly predict mathematical literacy at either point of measurement (see Table 4). In other words, whether a student generally tended to endorse or to reject vocational activities did not directly contribute to her or his mathematical literacy. In the cross-sectional and the longitudinal analyses, consistent with our findings for the scale scores, the things/people dimension emerged to be a significant predictor of mathematical literacy. The proportion of variance explained was $R^2 = .035$ at T1 and $R^2 = .076$ at T2.

As shown in Table 4, the angular peak was estimated to be $\theta = 353°$ and $\theta = 351°$ in the cross-sectional and longitudinal analysis, respectively. The effect amplitude was $A = 0.28$

Table 3
Multiple Regression of Mathematical Literacy (ML) at T1 and T2 on Interest Scale Scores and Covariates

	Scale Scores		Covariates		Scale Scores With Covariates	
	ML T1 b (SE)	ML T2 b (SE)	ML T1 b (SE)	ML T2 b (SE)	ML T1 b (SE)	ML T2 b (SE)
R	0.24 (0.11)*	0.34 (0.16)*			0.15 (0.12)	0.15 (0.15)
I	0.06 (0.13)	0.11 (0.18)			0.07 (0.12)	0.05 (0.16)
A	–0.26 (0.10)**	–0.37 (0.14)**			–0.19 (0.10)†	–0.18 (0.14)
S	–0.04 (0.12)	–0.22 (0.18)			0.06 (0.12)	–0.18 (0.18)
E	0.05 (0.09)	0.01 (0.14)			–0.02 (0.09)	0.04 (0.13)
C	–0.05 (0.09)	–0.01 (0.13)			–0.01 (0.09)	0.03 (0.12)
Gender			0.62 (0.15)**	0.33 (0.20)	0.46 (0.18)**	0.08 (0.24)
ML T1				0.77 (0.11)**		0.73 (0.11)**
Constant	–0.07 (0.09)	0.36 (0.15)*	–0.34 (0.11)**	–0.39 (0.14)**	–0.28 (0.12)*	–0.34 (0.16)*
R^2	.092	.137	.096	.344	.128	.384
$F(df1, df2)$	$F(6, 24.52) = 8.95^{**}$	$F(6, 17.55) = 7.99^{**}$	$F(1, 166) = 17.695^{**}$	$F(2, 18.34) = 79.84^{**}$	$F(7, 42.22) = 30.55^{**}$	$F(8, 14.63) = 18.94^{**}$
$\triangle R^2$					.032	.040
$F(df1, df2)$					$F(6, 43.21) = 1.96^{\dagger}$	$F(6, 20.71) = 2.25^{\dagger}$

Note. $\triangle R^2$ and the corresponding F statistic refer to the comparison of the "Covariates" models with the corresponding "Scale Scores with Covariates" models.
† $p < .10$. * $p < .05$. ** $p < .01$.

Table 4
Multiple Regression of Mathematical Literacy (ML) at T1 and T2 on Interest Profile Parameters (Level and Unweighted Interest Orientation) and Covariates

	Interest Profiles		Interest Profiles With Covariates	
	ML T1 *b* (*SE*)	ML T2 *B* (*SE*)	ML T1 *b* (*SE*)	ML T2 *b* (*SE*)
Level	0.00 (0.13)	–0.19 (0.19)	0.02 (0.13)	–0.19 (0.17)
T/P	0.28 (0.12)**	0.56 (0.17)**	0.09 (0.13)	0.30 (0.16)†
D/I	–0.03 (0.12)	–0.08 (0.17)	0.05 (0.12)	–0.04 (0.15)
Gender			0.58 (0.17)**	0.16 (0.22)
ML T1				0.76 (0.10)**
Constant	–0.07 (0.09)	–0.33 (0.13)*	–0.32 (0.11)**	–0.38 (0.14)**
Derived Angular Parameters				
Amplitude	0.28 (0.12)*	0.56 (0.16)**	0.11 (0.12)	0.30 (0.17)†
Peak	353°	351°	29°	353°
R^2	.035	.076	.101	.367
F(*df*1, *df*2)	*F*(3, 62.91) = 5.18**	*F*(3, 20.64) = 5.86**	*F*(4, 850.99) = 69.10**	*F*(5, 15.70) = 27.34**
$\triangle R^2$			.005	.023
F(*df*1, *df*2)			*F*(3, 888.52) = 0.12	*F*(3, 23.51) = 1.32

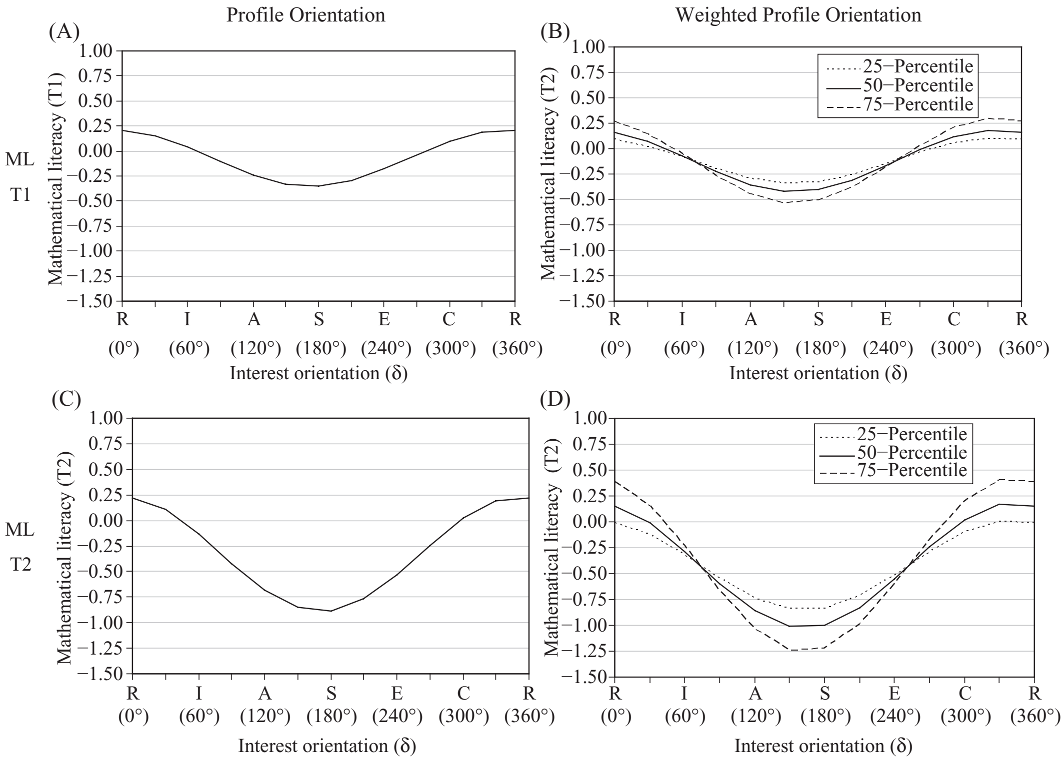
Note. T/P = things/people score; D/I = data/ideas score. $\triangle R^2$ and the corresponding *F* statistic refer to the comparison with the "Covariates" models in Table 3.
† $p < .10$. * $p < .05$. ** $p < .01$.

at T1 and $A = 0.56$ at T2, meaning that individuals with an interest orientation equal to θ scored 0.28 and 0.56 points above the mean of the literacy test at T1 and T2, respectively. Figure 3 (panels A and C) gives a graphical description of the derived associations. The amplitude follows a sinusoidal path, with a maximum close to the location of Realistic interests, decreasing until it reaches its maximal distance from the peak (artistic/social orientation) and then increasing again with proximity to the peak.

Table 4 also includes the interest profiles with covariate models. The results were similar to those reported for the scale score models. When gender and prior abilities were controlled, relations between things/people and data/ideas dimensional scores and mathematical literacy at T1 were not significant. As a consequence, the effect amplitude was no longer statistically significantly different from zero. Predicting T2 mathematical literacy yielded a significant *A* parameter at the $p < .10$ level, although the $\triangle R^2$ statistic was not significant.

Finally, we examined the power of interest profiles including level and orientation weighted by differentiation to predict mathematical literacy (see Table 5 and Appendix, Equation 2). Note that the absolute values of the regression coefficients derived for the unweighted and weighted things/people (cosine) and data/ideas (sine) orientations are not directly comparable because weighting changes the metric of the predictor variables. Interest level did not play a significant role in predicting mathematical literacy directly at either time. However, the things/people dimension again proved to be a powerful predictor of mathematical literacy at T1 and T2. The amount of variance explained was $R^2 = .059$ at T1 and $R^2 = .114$ at T2. The angular peak was comparable at T1 ($\theta = 339°$) and T2 ($\theta = 343°$). These parameter estimates were again closely in line with our hypotheses.

Figure 3
Predicted Mathematical Literacy (ML) at T1 and T2 (rows) by Unweighted Profile Orientation and Profile Orientation Weighted by Amplitudes (columns)



Note. The moderating function of profile amplitudes is represented by including regression lines at the 25th, 50th, and 75th percentile of the amplitude distribution. R = Realistic; I = Investigative; A = Artistic; S = Social; E = Enterprising; and C = Conventional.

Figure 3 (panels B and D) summarizes the relations estimated between orientation, differentiation, and mathematical literacy. The highest outcomes were expected at interest orientations close to the Realistic domain and the lowest at locations between the Artistic and Social domains. The moderating function of the amplitude is represented by including regression lines at the 25th, 50th, and 75th percentile of the amplitude distribution (see panels B and D). The higher the amplitude, the higher the change in predicted mathematical literacy as a student's profile orientation diverges from the peak. This moderating role of interest differentiation is most evident at T2.

In the last step, we included the covariates gender and prior abilities. As shown in Table 5, controlling for gender resulted in nonsignificant relations between interest profiles and mathematical literacy at T1. The same did not apply to the longitudinal analysis. Here, interest orientations predicted mathematical literacy even when prior abilities and gender were controlled. The estimated relation revealed a peak quite similar to that emerging from the analysis without covariates (i.e., $\theta = 347°$) but a somewhat smaller effect amplitude.

Table 5
Multiple Regression of Mathematical Literacy (ML) at T1 and T2 on Interest Profile Parameters (Level and Interest Orientation Weighted by Differentiation) and Covariates

	Interest Profiles		Interest Profiles With Covariates	
	ML T1 b (SE)	ML T2 b (SE)	ML T1 b (SE)	ML T2 b (SE)
Level	0.01 (0.13)	–0.15 (0.19)	0.02 (0.13)	–0.16 (0.17)
T/P	0.14 (0.05)**	0.27 (0.07)**	0.08 (0.05)	0.15 (0.06)*
D/I	–0.05 (0.05)	–0.08 (0.08)	–0.03 (0.05)	–0.04 (0.06)
Gender			0.51 (0.16)**	0.12 (0.21)
ML T1				0.74 (0.10)**
Constant	–0.12 (0.09)	–0.42 (0.13)**	–0.45 (0.11)**	–0.38 (0.14)**
Derived angular parameters				
Amplitude	0.15 (0.05)**	0.28 (0.07)**	0.08 (0.05)	0.16 (0.06)**
Peak	339°	343°	337°	347°
R^2	.059	.114	.112	.379
$F(df1, df2)$	$F(3, 30.10) = 43.21$**	$F(3, 19.29) = 10.67$**	$F(4, 78.78) = 53.93$**	$F(5, 15.66) = 28.01$**
$\triangle R^2$			.016	.035
$F(df1, df2)$			$F(3, 82.25) = 1.16$	$F(3, 23.32) = 3.84$*

Note. T/P = things/people score; D/I = data/ideas score. $\triangle R^2$ and the corresponding F statistic refer to the comparison with the "Covariates" models in Table 3.
† $p < .10$. * $p < .05$. ** $p < .01$.

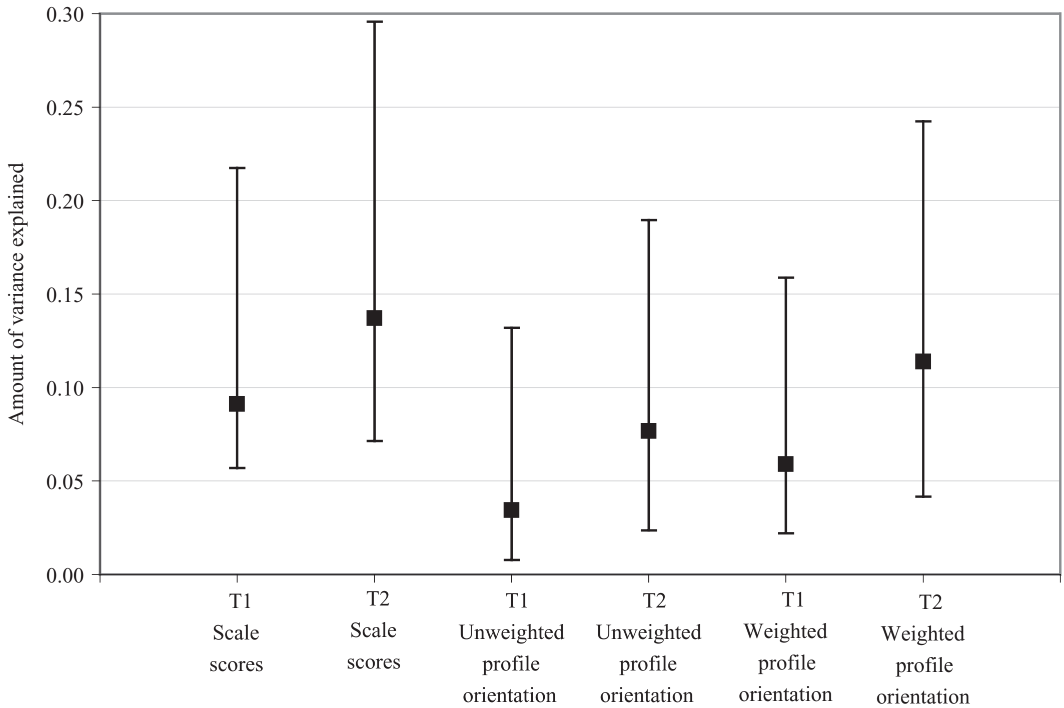
Most importantly, conceptualizing interests as weighted profiles proved to be the most robust approach because these variables significantly increased the predictive power of the baseline measures gender and prior abilities, as indicated by the significant $\triangle R^2$ statistic and the significant effect amplitude $A = 0.16$.

Validity of Interest Profiles

A main focus of our study was to examine the validity of reducing the scale score model to interest profiles. To this end, we compared the R^2 statistics provided by the different prediction models without the covariates gender and prior abilities. Figure 4 summarizes the mean R^2 estimates as well as their 95% confidence intervals. The scale score models explained a greater amount of variance than the interest profiles. However, their 95% confidence interval overlapped to a large degree. Thus, the generally higher R^2 statistics do not necessarily mean that using the reductionist profile approach results in a less valid representation of interests.

For the T1 outcomes, the mean R^2 estimates were estimated at .092 (scale score model), .035 (unweighted profile model), and .059 (weighted profile model). A closer look at Figure 4 suggests meaningful differences in the R^2 estimates given by the scale score model and the unweighted profile models. The mean estimate given by the unweighted profile model is outside the 95% confidence region of the scale score model (.057 to .217). However, the picture looks quite different when the scale score model is compared with the weighted

Figure 4
Amount of Variance Explained, R^2, in The Regression Analyses With Vocational Interest as Predictors of Mathematical Literacy



Note. Vertical lines depict nonsymmetrical 95% confidence intervals for the R^2 statistics.

profile model. Here, the mean R^2 estimate given by the weighted profile model is within the confidence region of the scale score model.

A quite similar picture emerges when considering the R^2 statistics for the longitudinal analyses. The mean R^2 of .076 provided by the unweighted profile model was only just within the 95% confidence interval of the R^2 derived from the scale score model (.071 to .296), but the mean R^2 given by the weighted profile model of .114 was well within the confidence region provided by the scale score model. This pattern suggests that the reductionist approach of using weighted profile orientations is likely to retain the most important information coded in the RIASEC scale scores. However, disregarding the profile differentiation in the unweighted model is likely to result in significantly lowered predictive power, meaning that disregarding profile differentiation excludes an important piece of information.

Figure 4 illustrates another important point. The confidence bands derived from the scale score models are wider than the corresponding bands given by the profile models. This means that the estimated prediction equations based on scale scores are less accurate than those of the (weighted) profile models. Furthermore, it is well known that application of regression models in small- to medium-sized samples with many variables as used here is likely to result in inflated R^2 statistics (e.g., Wherry, 1931). Hence, the results reported indicate that the weighted profile models achieve a good balance between reducing bias in R^2 estimates and enhancing the accuracy of prediction (i.e., narrowing the confidence bands).

Discussion

This study investigated the relations of vocational interests and mathematical literacy from both a cross-sectional and a longitudinal perspective using two different approaches: a scale score model based on Holland's RIASEC variables and interest profiles derived from a dimensional representation of Holland's model. Both methods yielded similar results. As expected, Realistic orientations were positively associated (e.g., Ackerman & Heggestad, 1997), whereas Artistic orientations were negatively associated with mathematical literacy. Findings were stable across both times of measurement. Our results thus emphasize the relevance of Realistic interests for students' mathematical literacy, further validating the focus of mathematical literacy on practical aspects that are important at work and in daily life.

One of our research objectives was to compare the scale score model with interest profiles as presented in a structural summary (c.f., Gurtman & Balakrishnan, 1998) and thus to examine the validity of reducing scale scores to interest profiles. Interest profiles derived from a dimensional representation of Holland's RIASEC model seem an attractive and valuable approach, particularly because these profiles allow aspects of interest orientations that predict a person's abilities positively or negatively to be identified. As mentioned above, the interest profile models and scale score models generated comparable results in terms of predictions of mathematical literacy. Nevertheless, when covariates were included in the regression analyses, only interest profiles were predictive for mathematical literacy above and above gender and prior abilities, indicating that interest profiles are more robust predictors than scale score models. Furthermore, weighted profile models resulted in R^2 values that were well within the 95% confidence intervals provided by the scale score models. Additionally, the R^2 statistics derived from the weighted profile models appeared to be much more precise than the corresponding values determined by the scale score models.

When the six scales scores are analyzed simultaneously, the structural aspect of Holland's RIASEC model is not considered. Because the scale scores show a specific correlation pattern, multicollinearity problems may occur in multiple regression analyses, and some associations may go undetected. For instance, when inspecting the scales individually, we found a negative correlation between interests in the Social domain and mathematical literacy in the longitudinal analysis. This prediction could not be confirmed in the results of the regression analyses including scale scores as predictors of mathematical literacy. Furthermore, it is well known that application of regression models in small- to medium-sized samples with many variables as used here is likely to result in inflated R^2 statistics (e.g., Wherry, 1931). Hence, the results reported indicate that interest profiles as presented in a structural summary provide a valid representation of interests with less biased R^2 estimates.

Additional profile analyses highlighted the relevance of interest differentiation. Weighted profile models explained a larger amount of variance than their unweighted counterparts. This result is perfectly in line with Holland's prediction that differentiation functions as a moderating variable. As our results show (see Figure 3), relationships between interest orientations and mathematical literacy are amplified in individuals with a high level of interest differentiation and greatly reduced in individuals with undifferentiated profiles. Thus, findings suggest that disregarding differentiation excludes an important piece of information. Weighted profile models are likely to retain the most important information coded in the RIASEC scale scores. In our study, we examined the moderating function of differentiation for the interest–ability relation in mathematical literacy. Further research is needed to examine the moderating role of differentiation for other outcome measures as well as further interest–outcome relations.

Likewise, Tracey and Robbins (2006) highlighted the need for further examinations of moderating variables within Holland's model. For example, they investigated direct and moderating relations of profile level on different outcome measures. Profile level was the third parameter in our profile analyses. Darcy and Tracey (2003) suggested that interest level (i.e., the general factor) indicates flexibility of interests. The results of our study are consistent with the findings of Prediger (1998) and Tracey and Robbins (2006), who could not confirm a direct association between level and outcomes. Profile level did not predict mathematical literacy in any of our regression analyses. Nevertheless, as proposed by Darcy and Tracey (2003) and confirmed by Tracey and Robbins (2006), the overall profile level should not be neglected in career counseling because it moderates the relationship between person–environment congruence and outcome measures.

Limitations and Outlook for Future Research

Mathematical literacy is known to be a key skill both at work and in daily life (National Council of Teachers of Mathematics, 1989). In this study, we examined the relations of vocational interests and mathematical literacy in a small sample of students from an academic-track school in Germany. Nevertheless, a meta-analysis reports positive associations between Realistic/Investigative interests and mathematical abilities for participants at various ages (Ackerman & Heggestad, 1997). These findings suggest that the association between Realistic interests and mathematical literacy may apply not only to students but to people of different ages and in different work environments. Further research is thus needed to test the stability of these findings in larger student populations as well as in nonstudent populations. Furthermore, the test of mathematical literacy implemented at our second point of measurement consisted of only eight items, and WLE reliability was not optimal. However, we believe that, given its good content validity, the achievement test used provides a reasonable assessment of the concept of mathematical literacy. Indeed, the TIMSS mathematical literacy test has been proved to be a valid measure (see I. V. S. Mullis et al., 1998) and has been frequently used in international and national large-scale assessments. We believe that the quite low test reliability resulted in rather conservative estimates. Hence, research aiming to replicate the current results should use other and longer test forms.

As the empirical results suggest, interest profiles derived from a dimensional representation of Holland's structural model allow aspects of interest orientations that predict a person's abilities positively or negatively to be identified. According to Ackerman

(1996), a more intense engagement with the object of interest leads to an increase in the corresponding skills and abilities. Therefore, it is necessary to investigate the processes mediating students' engagement in mathematical literacy. Likewise, studies have not yet examined interests in conjunction with other constructs relevant to the enhancement of abilities, such as self-concept or self-efficacy; further research is needed here.

We examined the relationships between interests and mathematical literacy using two different approaches: a scale score model and interest profiles. A promising avenue for future research would be to investigate how vocational interests predict other abilities thought to be important at work and in daily life, such as communication or reading skills. Although scale score models and interest profile models revealed quite similar results in our study, further evidence for the validity of reducing scale scores to profiles with other outcome measures is required.

This study was the first to demonstrate that vocational interests predict mathematical literacy both cross-sectionally and longitudinally, while additionally providing evidence for the validity of reducing Holland's scale score model to interest profiles.

Appendix

Prediction Equations for Interest Profiles

The regression models used in our study belong to a distinct class of regression analyses, namely, periodic regression (e.g., Batschelet, 1981). As outlined by Nagy et al. (IN PRESS), an individual's (i) things/people score can be denoted as $\alpha_i \times \cos(\delta_i)$ and his or her data/ideas score as $\alpha_i \times \sin(\delta_i)$. In periodic regression, the criterion variable is predicted by a linear combination of sine and cosine variables.

First of all, we disentangled interest orientation δ from interest differentiation α and tested a simple profile model that considered only interest level τ and profile orientation. It can be formalized as follows:

$$y_i = b_0 + b_1\tau_i + b_c\cos(\delta_i) + b_s\sin(\delta_i) + e_i = b_0 + b_1\tau_i + A\cos(\delta_i - \theta) + e_i. \qquad (1)$$

where b_0 denotes the regression intercept and thus the mean value of the outcomes across the entire range of the profile orientation δ at a value of $\tau = 0$, b_1 is the regression coefficient of τ and captures change in the outcome as a function of individual interest level, b_c is the coefficient of the cosine dimension $\cos(\delta_i)$, b_s is the coefficient of the sine dimension $\sin(\delta_i)$, and e is a regression residual. Equation 1 can be modified by a transformation of the model parameters, such that the derived parameters can be interpreted directly. The peak θ represents the interest dimension that is most positively associated with the given criterion variable. A reflects the effect amplitude and thus the difference in the expected outcome measures between individuals with an interest orientation equal to the peak θ and the mean value of the outcome across all possible orientations.

Equation 1 can be extended by the parameter α. Weighting $\sin(\delta_i)$ and $\cos(\delta_i)$ by differentiation α corresponds to the things/people and data/ideas scores. The extended Equation 2 makes it possible to examine the extent to which this weighting improves the prediction of a criterion variable:

$$y_i = b_0 + b_1\tau_i + b_c\alpha_i\cos(\delta_i) + b_s\alpha_i\sin(\delta_i) + e_i = b_0 + b_1\tau_i + A\alpha_i\cos(\delta_i - \theta) + e_i. \quad (2)$$

The parameters of the model above can be interpreted analogously to those of the model in Equation 2. However, the model given in Equation 2 includes profile differentiation as a moderator. As a consequence, A reflects the effect amplitude at a value of $\alpha = 1$.

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