

Choosing Psychology or Avoiding Mathematics: Integrating the Effects of Aligning and Diverging Interest Patterns on Study Choice

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Abstract

A good person – environment (PE) interest fit between a student and a (major) study program improves study outcomes. Indeed, PE interest fit empowers study counseling, supporting students to achieve greater satisfaction and better performance in the chosen program. However, existing PE interest fit methods focus exclusively on aligning patterns with programs of interest, while overlooking how students diverge from programs that are less of interest. To update literature, the present study ($N = 14,175$ students, $n = 31$ study programs) operationalizes and measures PE interest fit using logistic regression PE interest fit (LRIF). This LRIF represents both alignment to a specific program as well as divergence from other programs. Our results show that LRIF renders a stronger criterion validity regarding study choice compared to more established methods like profile correlation. In doing so, LRIF also yields upgraded incumbent E (environment) - profiles that represent both choosing a specific program as well as not choosing other programs. We consider that such an LRIF incumbent E – profile contributes to a stronger PE interest fit concept.

Keywords

vocational interests, RIASEC, PE interest fit, study choice, higher education

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Person-environment (PE) interest fit theories suggest that students strongly desire to achieve a match between their vocational interests and their (major) study program (Holland, 1997). A better understanding of PE interest fit can help students in making informed decisions about their academic path towards a suited study program (Schelfhout, Wille, Fonteyne, Roels, De Fruyt et al., 2021). Such a match also renders multiple boons for students, as a fitting environment improves the chances of beneficial outcomes such as greater satisfaction (Messerer et al., 2025), greater motivation (Nye et al., 2021) and better academic achievement (de Vries, Meeter, Jansen, & Huizinga, 2024). Due to these beneficial outcomes, PE fit has become a key component of study advice, especially relevant in open access environments with little to no enrolment restrictions (Pinxten et al., 2015).

Following such advice, students opt to enrol in a specific study program like Psychology, while simultaneously foregoing enrolment in alternative programs such as Economics or Mathematics (Feldman et al., 2001; Weidman, 2005). On the one hand, potential Psychology students show vocational interest patterns that align with the Psychology program. On the other hand, these potential students also show interest patterns that diverge to various degrees from other study programs like Economics or Mathematics. As such, this theoretical dichotomy addresses a fundamental question in the study choice process. Do students choose a program like Psychology because they are genuinely interested? Or do students choose Psychology because they want to avoid programs of less interest like Economics or Mathematics? Indeed, interest patterns of the study programs that students do not choose can additionally impact the study choice processes of exploration and decision-making (de Vries, Meeter, Jansen, & Huizinga, 2024).

To the present day, diverging interest patterns that lead away from non-chosen study programs are all but neglected by literature, as we have no knowledge of a PE interest fit operationalization or measure that integrates the overlooked diverging patterns with the ubiquitous aligning patterns. As misfit is an inherent part of PE interest fit theory (De Cooman & Vleugels, 2022), we argue that this neglect warrants an update of the state of the art. Although divergence is not identical to traditional notions of interest misfit, both concepts reflect reduced correspondence between an individual's interests and an educational environment. Whereas misfit reflects insufficient alignment with the focal study program, divergence also reflects (the absence of) alignment with alternative study programs.

This neglect of divergence holds considerable risk as an operationalization or measurement of PE interest fit exclusively based on aligning interest patterns underrepresents study choice processes. Additionally, literature on opportunity cost neglect also refers to the foregone benefit of options not chosen (Persson & Tinghög, 2020). Ignoring diverging interest patterns can thus lead to choices that are suboptimal because not all relevant alternatives are represented or considered (Greenberg & Spiller, 2016). In a higher education (open access) context, a sub-optimal study choice can increase the student's chance to fail and drop out (de Vries, Meeter, & Huizinga, 2024).

The present study proposes to model the outcome of the study choice process by integrating aligning and diverging interest patterns that can lead to a specific study program. We start by deriving a novel method for operationalizing and measuring PE interest fit from the already proven method of regressed fit (Edwards, 1993; Schelfhout, Bassleer, et al., 2022). Using the data of $N = 14,175$ students, spread out over $n = 31$ study programs, we then provide proof-of-concept that the logistic regression method relates more strongly to the criterion of study choice than established PE interest fit measures.

Vocational Interests Patterns of Person and Environment

In a higher education context, vocational interests refer to an individual's preferences for (1) study-related activities such as analyzing a statistical problem and (2) future professions like being a nurse (Dutry et al., 2025; Hanna et al., 2025). To categorize and understand an individual's vocational interests, the RIASEC model of Holland (1997) functions as one of the most influential frameworks (Nauta, 2010). The circumplex model covers six vocational interest dimensions: Realistic (R), Investigative (I), Artistic (A), Social (S), Enterprising (E), and Conventional (C). A RIASEC interest questionnaire can provide personal profile scores for each of the six vocational interest dimensions (Fonteyne et al., 2017; Holland, 1997).

The RIASEC model also allows us to obtain environment profile scores linked to environments such as study programs. In higher education, the incumbent method can thus capture the interest dimensions of a specific study program, based on the interests of the incumbent students that enroll for that specific program (Allen & Robbins, 2010; Tracey et al., 2012)¹. To obtain a study program interest profile, researchers can average out student scores on each of the six RIASEC dimensions.

As a result, the RIASEC patterns of students and the RIASEC patterns of study programs yield commensurate measurements, as both patterns are scored on the same RIASEC scale (Schelfhout et al., 2019). This commensurability aspect enables the fit of a student to a study program (Quinlan & Corbin, 2023). For the present study, we consider two congruence-based, established PE interest fit methods that align the student to the study program profile using all six RIASEC dimensions.

Euclidean Distance and Correlation Coefficient

First, Euclidean distance measures the distance between person and environment interest profiles in Euclidean space (Schelfhout, Wille, Fonteyne, Roels, Derous, et al., 2021), resulting in a continuous measure of PE interest fit (i.e., ED) (Schelfhout, Bassleer, et al., 2022). A lower distance indicates greater congruence. Second, the profile correlation method also provides a continuous PE interest fit measure (i.e., PC). This measure calculates the correlation coefficient between an individual's RIASEC scores and those of the environment (Xu & Li, 2020). Research demonstrates that a lower ED or a higher PC between a student's RIASEC profile and a study program interest profile increases the likelihood that the student ultimately selects that study program (Su & Rounds, 2015). Note that PC outperforms other PE interest fit measures (such as ED) in predicting career outcomes like job and life satisfaction (Xu & Li, 2020).

Though both measures clearly have merit, these measures require predetermined environment interest profiles. These E – profiles are essential to calculate the PE interest fit between a prospective student and a study program (Schelfhout, Wille, Fonteyne, Roels, De Fruyt et al., 2021). Researchers usually obtain study program E – profiles by using incumbent averages or expert scores on each of the dimensions (Rounds et al., 1999). However, such E – profiles do not account for the inherent and important variance and covariance within and between RIASEC dimensions (Nye, Perlus, & Rounds, 2018; Tracey et al., 2012). This limitation instigated the use of other PE fit methods that are more fine-grained (van Vianen, 2018).

Regressed PE Interest Fit

One such method is polynomial regression in which outcomes like performance or choice are regressed on a combination of person -and environment scores (Edwards, 1993). Polynomial regression methods yield a more powerful assessment of PE interest fit, as studies report stronger

prediction and criterion validity regarding outcomes like academic achievement (Nye, Butt, et al., 2018; Nye, Prasad, et al., 2018). Schelfhout, Bassleer and colleagues (2022) demonstrated that when PE fit is estimated within a single environment, the effects of the environment scores become fixed. Under these circumstances, the polynomial regression model can be algebraically reformulated into a student-level regressed interest fit (RIF) function that depends only on an individual's six RIASEC scores. Although the environmental profile no longer appears as a separate predictor, the regression coefficients that define the RIF function retain the information about the environment. These regression coefficients thus constituted a novel way to represent an environment profile. Collecting additional data for predetermined profiles is therefore no longer necessary as RIF can inherently generate an environment interest profile for each study program, taking into account the variance within and covariance between interest dimensions (Schelfhout, Wille, Fonteyne, Roels, De Fruyt, et al., 2021). Moreover, RIF returns a personal fit score for each student within a specific study program by applying the environment-specific regression coefficients to the student's RIASEC profile. The present study builds on this RIF single-environment adaptation of polynomial regression.

Although RIF further refines the generation of environment interest profiles within one specific program, RIF still does not account for the influence of interest patterns that can lead students away from other study programs. As an example, RIF can model how well the RIASEC pattern of Psychology students aligns with the RIASEC pattern of the Psychology program. However, RIF still cannot simultaneously model how the RIASEC pattern of Psychology students diverges from the RIASEC pattern of other programs like Mathematics or Economics. And yet, during the study choice process of exploration (de Vries, Meeter, Jansen, & Huizinga, 2024), both types of patterns can prove decisive towards the ultimate study choice. For the present study, we therefore propose to modify RIF to integrate both types of interest patterns, from chosen and non-chosen programs.

Deriving Logistic Regressed PE Interest Fit

To integrate interest patterns that align with a study program like Psychology and interest patterns that diverge from other programs, we present the logistic regressed interest fit (LRIF) method, derived from the adapted student – level RIF method. The LRIF method uses a binary study choice criterion. The students that choose a study program like Psychology have aligning interest patterns that lead towards Psychology, and thus a criterion value of 1. The students that do not choose Psychology have diverging patterns away from Psychology, towards other programs, and thus a criterion value of 0. Future Psychology students therefore need to align with the pattern represented by criterion 1 and diverge from the pattern(s) represented by criterion 0. As shown in equation (1), we represent the integration of both types of interest patterns by the set of regression weights of a logistic regression,

$$P(S) = \frac{e^{\beta_0 + \beta_1 R + \beta_2 I + \beta_3 A + \beta_4 S + \beta_5 E + \beta_6 C}}{1 + e^{\beta_0 + \beta_1 R + \beta_2 I + \beta_3 A + \beta_4 S + \beta_5 E + \beta_6 C}}, \quad (1)$$

with S being a binary variable that can take the value 1 (i.e., choosing the study program) or 0 (choosing another study program), $P(S)$ returning the probability of choosing the study program, and with R to C representing the student scores on the RIASEC dimensions. β_0 to β_6 are regression coefficients and need to be estimated. Note that the expression in the exponent of Euler's number is linear in its parameters (Edwards, 1993; Nye, Prasad, et al., 2018). Also, LRIF only uses individual linear RIASEC terms in the exponent of the logistic regression. As such, the method limits the number of predictors, minimizing type I errors (Su et al., 2019). In fact, the entire

logistic regression can also be written as a linear expression by using a logit transformation of the odds ratio as displayed in equation (2):

$$\text{logit}(P) = \ln\left(\frac{P}{1-P}\right) = \beta_0 + \beta_1 R + \beta_2 I + \beta_3 A + \beta_4 S + \beta_5 E + \beta_6 C, \quad (2)$$

with P again returning the probability of choosing the study program, $1 - P$ returning the probability of choosing another study program, and with R to C representing the student scores on the RIASEC dimensions. Once the regression scores are established, we can measure an LRIF for each (prospective) student with a specific study program by inserting the student RIASEC scores in equation (1). The return of the function is a value between 0 and 1 that represents (1) the probability of a student choosing the specific program and therefore also (2) the PE interest fit of the student with the specific study program. This score thus represents both how well a potential student aligns with interest patterns that lead to Psychology, as well as how hard the potential student diverges from interest patterns that do not lead to Psychology but to other programs such as Mathematics or Economics.

Present Study

The present study proposes and evaluates the LRIF method that merges aligning and diverging vocational interest patterns into a novel measure of PE interest fit. The LRIF method therefore operationalizes PE interest fit as (1) aligning with program interest patterns that lead to choosing the program and at the same time as (2) diverging from program interest patterns that do not lead to choosing the program. Literature on interest fit theory (De Cooman & Vleugels, 2022; Holland, 1997), opportunity cost neglect (Greenberg & Spiller, 2016; Persson & Tinghög, 2020), and study choice processes (de Vries, Meeter, Jansen, & Huizinga, 2024) indicates that we should include diverging interest patterns into PE interest fit operationalization and measurement to avoid suboptimal fit measures. We therefore hypothesize that the LRIF method will show stronger (incremental) criterion validity towards study choice compared to the PC method and the ED method.

Materials and Methods

Data Availability and Ethics Statement

We followed the journal article reporting standards (JARS) for quantitative research in psychology (Appelbaum et al., 2018). We may not disclose the data as stipulated in the approved specific ethical protocol (application number 2016/82, Ethics Committee of the Faculty of Psychology and Educational Sciences, Ghent University). Data were collected online. Students had to explicitly accept the general terms and conditions, in which was clearly stated that their personal data could be used for scientific research. Data were analyzed using SPSS version 28.0 (IBM Corp, 2023) and R (R Core Team, 2026). The present study's design and analyses were not preregistered.

Participants

The present study analyzed data from a Western European university ranked in the top 100 in the ARWU ranking 2025 (<https://www.shanghairanking.com/rankings/arwu/2022>). The university has eleven faculties offering 42 bachelor's programs, with low tuition fees around € 1,200 or

about \$ 1,400 in an open access system². First-year students at this university follow a uniform curriculum within their chosen study program. These study programs are largely independent and stratified, so that a student that chooses psychology will also graduate as a psychologist, provided the student passes the required (yearly) examinations. Consequently, the study program environments of the present study are well-suited to ascertain the unique influence of vocational interests on study choice as the possible biases of ability-based selection and costs are minimal.

At the start of each academic year, first-year higher education students are strongly encouraged to complete an online RIASEC questionnaire that identifies their vocational interests. The secondary data are part of the longitudinal university-wide study (re)orientation and remediation SIMON project (Fonteyne, 2017; Schelfhout, Wille, et al., 2022). We included study programs with a sample size of at least 110 first-year students, as we considered 50 students as a baseline, while adding ten students for each predictor in the model (Peduzzi et al., 1996). As such, the dataset for the present study included data on $N = 14,175$ students (60% female, $M_{\text{age}} = 18$) spread out over $n = 31$ study programs and three consecutive academic years (i.e., from 2016 to 2019).

RIASEC Dimensions of Vocational Interests

We assessed the dimensions of the RIASEC model (Holland, 1997) using the SIMON-I instrument (Fonteyne et al., 2017). The SIMON-I instrument includes 173 items across six RIASEC dimensions. The instrument consists of yes (1) or no (0) questions that ask students whether they would be interested in engaging in specific activities or pursuing particular occupations. The realistic dimension (R) was assessed through 27 items (e.g., developing electronic systems, pilot; $\alpha = .93$), the investigative dimension (I) through 33 items (e.g., analyzing statistics, researcher; $\alpha = .88$), the artistic dimension (A) through 30 items (e.g., designing webpages, photographer; $\alpha = .92$), the social dimension (S) through 32 items (e.g., giving travel advice, teacher; $\alpha = .92$), the enterprising dimension (E) through 26 items (e.g., organizing a conference, lawyer; $\alpha = .93$) and the conventional dimension through 25 items (e.g., calculating prices, judge; $\alpha = .91$). To calculate the final student score on each dimension, the number of “yes” answers for that dimension was summed and divided by the total number of items for that dimension. This quotient was then multiplied by 100 to obtain a score between 0 and 100. The higher the score on a RIASEC dimension, the stronger the preference for that area of interest. The RIASEC dimensions were used as the independent variables in the LRIF method.

Predetermined Study Program RIASEC E – Profiles

We captured the interest dimensions of each study program based on the interests of successful and persistent students, who were satisfied with their study choice (Allen & Robbins, 2010; Holland, 1997; Schelfhout et al., 2019; Tracey et al., 2012). These predetermined E – profiles were needed to calculate both ED as well as PC. To determine these predetermined E – profiles, we used an independent dataset of third-year students who obtained a bachelor’s degree from the same study programs in 2016 or earlier, originating also from the SIMON project. We established each program’s RIASEC profile by averaging the RIASEC scores of student incumbents who were nearing graduation. For detailed information on the study program RIASEC profiles and sample sizes, we refer to the Supplementary Information (SI) Table T1.

Study Choice

Before completing the RIASEC questionnaire, students had to indicate their chosen study program in their first year of higher education (therefore, we also knew students’ non-chosen

study programs). For each specific program, study choice thus functions as a binary, dependent criterion for the LRIF method (1 = choosing the study program, 0 = choosing another study program).

Analyses

For PC and ED, we operationalized PE interest fit as the match between the student RIASEC profile and the predetermined study program RIASEC profile. For PC, we measured PE interest fit as the correlation coefficient between a student's profile and the predetermined study program profile. A higher PC indicates a better PE interest fit. For ED, we measured PE interest fit as the Euclidean distance between a student's profile and the study program profile. A lower ED indicated a better PE interest fit (see SI for technical information on how to calculate Euclidean distance).

For LRIF, we operationalized PE interest fit towards one specific study program as (1) aligning with program interest patterns that lead to choosing the program and at the same time as (2) diverging from program interest patterns that do not lead to choosing the program. We regressed the dependent variable study choice onto the standardized scores of the six RIASEC variables. For each of the 31 study programs, we matched the students that chose the specific study program (i.e., study choice criterion = 1) with an equally large and random group of students that did not choose the study program (i.e., study choice criterion = 0). For each of the 31 study programs, we estimated the regression coefficients for the study program RIASEC terms, representing the specific LRIF study program interest profile. We measured the LRIF PE interest fit for a (non-) student in a specific study program by multiplying the student RIASEC term scores with the corresponding coefficients from the program-specific logistic regression, after which the six products were summed. This procedure resulted in the students' logit scores, which were then converted to probability scores by combining equations (1) and (2) from the Introduction. A higher LRIF value indicates a better PE interest fit. The specific LRIF study program interest profiles are listed in the SI, [Table T2](#).

We used two measures to assess the regression fit between the RIASEC data and the study choice data. First, we evaluated the goodness of fit for each regression with a Nagelkerke's R^2_{Nag} (Nagelkerke, 1991). The closer R^2_{Nag} is to one, the better the fit of the model (Hosmer & Lemeshow, 2000; Nagelkerke, 1991). Second, we plotted ROC (receiver operating characteristic) curves for each regression to show the classification accuracy of our LRIF models. For this purpose, we used the associated Area Under the ROC Curve (AUC) values, where $.70 < AUC \leq .80$ is acceptable, $.80 < AUC \leq .90$ is excellent, and $AUC > .90$ is considered outstanding (Hosmer & Lemeshow, 2000). For a detailed overview of all ROC curves, we refer to the SI, [Figure F1](#).

To test our hypothesis that the LRIF method will show a stronger criterion validity towards study choice, we performed two sets of analyses on criterion validity and incremental criterion validity. For criterion validity, we calculated the point-biserial correlations between the study choice criterion and the PC, ED, and LRIF PE interest fit measures for each study program. We then performed a series of three paired-sample, two-sided *t*-tests on the rendered correlations across $n = 31$ programs, with the standard error adjusted by the correlation between measures, and with a Cohen's *d* indicating effect size. We interpreted the effect sizes analogue to Sawilowsky (2009): $d = 0.01$ (very small), $d = 0.20$ (small), $d = 0.50$ (medium), $d = 0.80$ (large), $d = 1.20$ (very large) and $d = 2.00$ (huge). The effect size indicates the difference in criterion validity.

For incremental criterion validity, we logistically regressed study choice on the LRIF, CD and ED (standardized) measures for each study program. As the (standardized) coefficients are

comparable within one (logistic) regression, but not between regressions, we conservatively extracted the regression coefficients and transformed the three coefficients into a 1 (the highest coefficient) or a 0 (the other coefficients). For instance, for the study program “Applied Linguistics” (see also Table 1), the β_{LRIF} coefficient in the LRIF regression was the highest coefficient compared to the β_{PC} and β_{ED} coefficients and thus transformed into a 1, while the other two coefficients are transformed into a 0. All transformations are listed in the SI, T3. We performed a series of three asymptotic McNemar paired-sample proportion tests across study programs to establish which of the three PE interest fit variables rendered the highest proportion of transformed 1-coefficients. These proportions indicate the incremental criterion validity of the PE interest fit measures, while controlling each other’s effects.

To conclude our analyses, we computed the correlation between the RIASEC study program profiles from the independent dataset and the RIASEC study program profiles generated through the LRIF method.

Results

Students who chose a specific program showed an average PE interest fit of $M_{\text{PC}} = .71$ ($SD = .28$), $M_{\text{ED}} = 84.05$ ($SD = 47.93$), and $M_{\text{LRIF}} = .70$ ($SD = .22$) with the specific program. Students who did not choose a specific program showed an average PE interest fit of $M_{\text{PC}} = .10$ ($SD = .50$), $M_{\text{ED}} = 150.84$ ($SD = 74.64$), and $M_{\text{LRIF}} = .30$ ($SD = .28$) with the specific study program. Table 1 shows the program-specific analyses of (1) the logistic regressions regarding LRIF and (2) regarding study choice, (3) the biserial correlations between study choice and our three PE interest fit measures, and (4) the correlations between the predetermined study program interest profiles, on which PC and ED were based, and the LRIF study program interest profiles.

Fit Evaluation

The R^2_{Nag} and the AUC statistics from Table 1 show that the logistic regressions on the data of $n = 31$ programs achieved at least an acceptable fit between the RIASEC predictors and the study choice criterion. As an example, Figure 1 shows that the ROC curve for the study program Communication Sciences manages to correctly classify 85% of the students who choose Communication Sciences (i.e., sensitivity) and about 82% of the students who choose another study program (i.e., specificity).

Hypothesis Testing

We tested the hypothesis that the LRIF method will show a better (incremental) criterion validity towards study choice compared to the PC method and the ED method. First, we performed three paired samples, two-sided t -tests on the point-biserial correlation coefficients over programs between ED, PC and LRIF and the study choice criterion (see also Table 1). Results showed (1) a significant difference between LRIF ($M = .63$, $SD = .13$) and PC ($M = .59$, $SD = .12$), $t(30) = 5.58$, $p < .001$, $d = 0.31$, (2) a significant difference between LRIF and ED ($M = .45$, $SD = .09$), $t(30) = 8.82$, $p < .001$, $d = 1.54$, (3) and a significant difference between PC and ED, $t(30) = 7.98$, $p < .001$, $d = 1.25$.

Second, we performed three McNemar paired-sample proportion tests on the transformed regression coefficients (i.e., 1 or 0) over programs of ED, PC and LRIF, derived from the logistic regression of study choice on ED, PC, and LRIF variables. Results showed a (1) a significant difference between the proportions of LRIF ($P = .81$, $SE = .08$) and PC ($P = .13$, $SE = .17$), $Z =$

Table 1. Study Programs, LRIF Fit, Logistic Regression Analyses, and E – Profile Correlations

Study program	$N_{students}$	LRIF		Regression of study choice (1/0) on LRIF, PC, and ED					$r_{biserial}$ with study choice (1/0)			r
		R^2		INT	β_{LRIF}	β_{PC}	B_{ED}	R^2_{NAG}	LRIF	PC	ED	E – profiles
		NAG	AUC									
Applied language studies	418	0.51	0.86	1.12	0.85	0.21	−0.29	0.54	0.64	0.59	−0.46	0.80
Art history	124	0.88	0.98	3.18	0.85	0.57	0.40	0.89	0.92	0.84	−0.49	0.98
Bio sciences	189	0.44	0.84	0.99	0.95	0.10	−0.52	0.50	0.61	0.57	−0.42	0.81
Biochemistry and biotechnology	202	0.47	0.85	1.01	0.81	0.22	−0.29	0.51	0.62	0.60	−0.47	0.89
Biology	123	0.44	0.83	0.97	0.43	0.39	− 0.46	0.50	0.59	0.59	−0.54	0.94
Biomedical sciences	481	0.43	0.84	0.90	0.73	0.27	−0.28	0.47	0.59	0.58	−0.42	0.96
Bioscience engineering	650	0.50	0.86	1.15	0.81	0.35	−0.15	0.51	0.64	0.61	−0.38	0.96
Business administration	868	0.65	0.92	1.64	0.75	0.31	−0.35	0.68	0.75	0.73	−0.68	0.92
Communication sciences	326	0.68	0.93	1.71	0.68	0.69	0.00	0.70	0.76	0.70	−0.46	0.91
Computer sciences	124	0.45	0.86	1.08	0.82	0.16	−0.41	0.52	0.62	0.57	−0.51	0.68
Criminological sciences	528	0.20	0.72	0.49	0.42	0.09	− 0.51	0.28	0.39	0.40	−0.41	0.61
Economics	1066	0.64	0.91	1.55	0.85	0.29	−0.28	0.66	0.75	0.73	−0.63	0.90
Educational sciences	363	0.73	0.94	1.83	0.85	0.29	−0.10	0.74	0.80	0.68	−0.62	0.88
Engineering	728	0.60	0.90	1.47	0.44	0.74	−0.20	0.64	0.72	0.72	−0.52	0.98
Engineering - architecture	179	0.73	0.94	2.15	1.53	−0.22	−0.50	0.75	0.80	0.67	−0.26	0.77
Engineering technology	935	0.76	0.95	2.18	0.99	0.36	−0.20	0.77	0.83	0.79	−0.52	0.86
History	231	0.29	0.79	0.62	0.84	0.16	−0.17	0.34	0.50	0.45	−0.28	0.70
Law	1017	0.38	0.81	0.85	0.67	0.27	−0.44	0.45	0.55	0.55	−0.43	0.80
Linguistics and literature	495	0.59	0.90	1.39	0.94	0.37	−0.04	0.61	0.71	0.62	−0.46	0.79
Medicine	557	0.35	0.80	0.73	0.94	−0.05	−0.53	0.40	0.52	0.45	−0.35	0.81
Oriental languages and cultures	152	0.28	0.76	0.55	0.47	0.28	−0.21	0.33	0.46	0.47	−0.39	0.67
Pharmaceutical sciences	664	0.36	0.80	0.77	0.53	0.33	−0.33	0.41	0.54	0.54	−0.41	0.85
Physical education and movement sciences	164	0.19	0.71	0.43	0.58	0.03	−0.48	0.26	0.38	0.25	−0.32	0.63
Physical therapy and motor rehabilitation	936	0.33	0.79	0.73	0.58	0.26	−0.40	0.40	0.51	0.52	−0.43	0.79

(continued)

Table 1. (continued)

Study program	$N_{students}$	LRIF		Regression of study choice (1/0) on LRIF, PC, and ED					$r_{biserial}$ with study choice (1/0)			r E – profiles
		R^2 NAG	AUC	INT	β_{LRIF}	β_{PC}	β_{ED}	R^2_{NAG}	LRIF	PC	ED	
Physics and astronomy	116	0.51	0.87	1.18	0.63	0.55	0.10	0.56	0.66	0.64	−0.48	0.78
Political sciences	239	0.34	0.80	0.78	0.75	0.17	−0.39	0.40	0.53	0.51	−0.40	0.84
Psychology	1417	0.42	0.83	0.83	0.37	0.51	−0.16	0.46	0.58	0.57	−0.49	0.95
Public administration and management	138	0.55	0.88	1.16	1.07	0.06	−0.29	0.57	0.67	0.61	−0.49	0.86
Sociology	126	0.45	0.84	0.92	0.72	0.38	−0.05	0.48	0.59	0.54	−0.40	0.81
Speech language and hearing sciences	193	0.56	0.88	1.23	0.50	0.70	0.25	0.60	0.69	0.64	−0.49	0.89
Veterinary medicine	426	0.33	0.79	0.68	0.65	0.18	−0.36	0.37	0.51	0.47	−0.40	0.78

Note. PE = person – environment, LRIF = logistic regressed PE interest fit, R^2_{NAG} = explained population variance (deviance), measured through Nagelkerke's pseudo R-squared (Nagelkerke, 1991), AUC = Area Under the Curve, INT = intercept, PC = correlation PE interest fit, ED = Euclidean distance PE interest fit. For the regression of study choice, the highest standardized coefficient is annotated in bold; for ED we consider the absolute value as low ED represents high fit. The last column presents the correlations between the predetermined study program E – profiles, on which PC and ED were based, and the LRIF study program E – profiles ($M = .83$, $SD = .10$).

3.90, $p < .001$, (2) a significant difference between the proportions of LRIF and ED ($P = .06$, $SE = .17$), $Z = 4.43$, $p < .001$, and (3) a non - significant difference between the proportions of PC and ED, $Z = .82$, $p = .41$.

Both results confirm our hypothesis that the LRIF method shows a stronger (incremental) criterion validity towards study choice compared to the more established methods used in literature like PC and ED.

Discussion

A better understanding of the congruence between students' vocational interests and study programs can help students in making informed decisions about their academic path (Nauta, 2010; Schelfhout, Wille, Fonteyne, Roels, De Fruyt, et al., 2021). Such informed decisions improve the chances of beneficial outcomes like higher academic achievement (Nye, Butt, et al., 2018; Schelfhout, Bassleer, et al., 2022), greater motivation (Nye et al., 2021) and greater satisfaction (Messerer et al., 2025). Until now, existing PE interest fit operationalizations and measurements only acknowledged interest patterns that align with a specific environment, ignoring (mis)fit with other environments (Allen & Robbins, 2010; Tracey et al., 2012). This omission goes against the core of conceptual PE interest fit theory, which does include misfit (De Cooman & Vleugels, 2022; Holland, 1997). For the present study, PE interest fit incorporates the extent to which a student's interests align with the focal study program, but also diverge from other study programs. Moreover, the omission overlooks the inherently competitive nature of study choice as choosing one program means foregoing others (Feldman et al., 2001; Weidman,

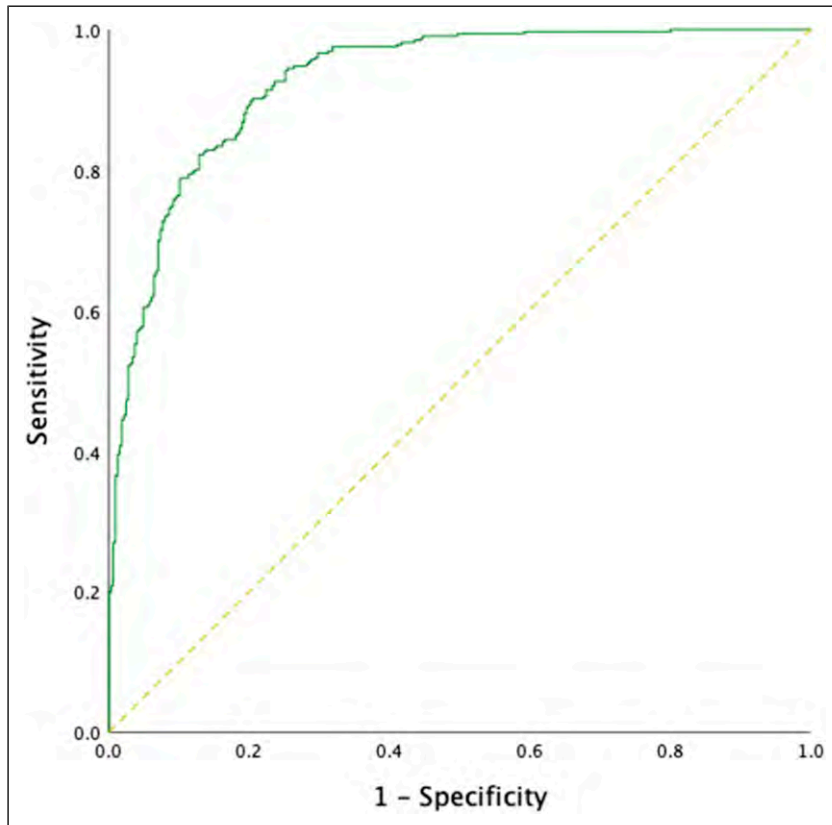


Figure 1. ROC Curve Study Program Communication Sciences.

Note. Sensitivity refers to the proportion of true positives, or the number of students correctly classified as Communication Sciences students. $1 - \text{Specificity}$ refers to the proportion of false positives, or the number of students incorrectly identified as Communication Sciences students. The green ROC curve delimits The Area Under the Curve (AUC). AUC is a measure of the model's ability to distinguish between students who choose Communication Sciences and students who choose another study program, in this case based on their PE interest fit (i.e., LRIF). The AUC value for this model is 92.70%. The yellow dotted reference line refers to the 50% probability level benchmark of distinction

2005). Interest patterns of the study programs that students do not choose, can indeed also have an impact on study choice processes of exploration and decision-making (de Vries, Meeter, Jansen, & Huizinga, 2024). Ignoring this practical reality can invoke opportunity cost neglect (Greenberg & Spiller, 2016; Persson & Tinghög, 2020), leading to suboptimal study choices that increase the chance of dropout or failure (de Vries, Meeter, & Huizinga, 2024).

To address this gap in literature, the present study proposed and evaluated the LRIF method that merges aligning and diverging vocational interest patterns into a novel measure of PE interest fit. We therefore expanded the method of regressed interest fit towards logistic regressed PE interest fit (LRIF). LRIF integrates interest patterns that (1) align with and lead to a specific study program (e.g., Psychology) and (2) interest patterns that diverge and lead away from other programs (e.g., Economy or Mathematics). The resulting PE interest fit measure represents the probability of a student choosing the specific program, based on aligning interests with the specific program and diverging interests from other programs, which can also lead to the specific program. As proof-of-concept, we applied LRIF to empirical data of $N = 14,175$ students, spread

out over $n = 31$ study programs. More specifically, we examined how well LRIF relates to the study choice criterion by comparing the LRIF performance to established methods like Euclidean distance PE interest fit (ED, see [Schelfhout, Wille, Fonteyne, Roels, Deros, et al., 2021](#)) and correlation PE interest fit (PC, see [Xu & Li, 2020](#)).

The present study shows that the LRIF method successfully updates the conceptualization of PE interest fit by including both diverging and aligning interest patterns. For each of the 31 study programs, the LRIF method obtains acceptable to outstanding model fits for the prediction of study choice. This finding implies that LRIF can effectively differentiate between students who choose a specific study program and those who choose another study program. For example, students that chose a specific study program show an LRIF that is more than twice as strong compared to students that did not choose the program. These results support the theoretical premise that individuals seek a match with their environment ([De Cooman et al., 2009](#); [Holland, 1997](#); [Oh et al., 2018](#)). For instance, the students in the present study averaged a $r_{PC} = .71$ with their study programs, which is consistent with literature on open access study environments ([Schelfhout et al., 2019](#)). As such, our results are also consistent with previous research that established positive associations between PE interest fit and work or study outcomes ([Nye, Butt, et al., 2018](#); [Nye, Prasad, et al., 2018](#); [Schelfhout, Bassleer, et al., 2022](#)).

LRIF also outperforms the more conventional continuous PE interest fit measures ED and PC, as LRIF shows a stronger criterion validity. In other words, LRIF provides a better explanation of the relation between the interests of students and the programs they (do not) choose. Between LRIF and ED, we observe a very large difference in explanative power, which remains consistent over most study programs. Between LRIF and PC, we observe a more modest difference, but also consistent over most study programs. These early results therefore align with the plea of researchers who endorse regression above traditional congruence ([Edwards, 1993, 1994](#); [Nye, Butt, et al., 2018](#); [Nye, Prasad, et al., 2018](#); [Schelfhout, Wille, et al., 2022](#)), with the understanding from the present study that both aligning and diverging interest patterns should be considered ([De Cooman & Vleugels, 2022](#); [Jansen & Kristof-Brown, 2006](#)). Although compelling, we consider the results of the present study preliminary evidence. Literature must call for more research to confirm, refute or adjust our findings, based on more broad datasets of different educational systems and even more diverse study programs.

Implications

First, the present study addresses study choice as a choice between study programs, which acknowledges the reality of the study choice process ([de Vries, Meeter, & Huizinga, 2024](#); [de Vries, Meeter, Jansen, & Huizinga, 2024](#)). Indeed, the differentiation of study programs regarding interest patterns represents the study choice students make in selecting as well as rejecting study programs. By design, the LRIF method complements the incumbent philosophy that the people make the environment ([De Cooman & Vleugels, 2022](#); [Hoff et al., 2020](#)). As an example, a stronger LRIF for a program like Psychology can thus indicate that a future student aligns with interest patterns that lead towards the Psychology program. However, a stronger LRIF can also indicate that the future student diverges from interest patterns that do not lead to the Psychology program, but to other programs like Economics or Mathematics. Important to note, the divergence can vary depending on specific study programs. On average, a psychology student's interests will diverge much more from interest patterns that lead to programs like Mathematics or Economics, than from interest patterns that lead to topically related programs such as Educational Sciences or Sociology.

Second, the presented LRIF method provides proof-of-concept that regression also enables operationalizing and measuring PE interest fit towards dichotomous criteria like study choice.

Consequently, we view LRIF as the direct analogue of RIF for binary study choice outcomes rather than as a distinct alternative. Moreover, given the binary nature of the mandatory criterion for LRIF, the method holds promise for use in any application that involves a choice between two (study) environments. For instance, LRIF can enable established study orientation programs at colleges or universities to answer the following student question: Am I more interested in a professionally oriented bachelor's program or an academically oriented bachelor's program?

As such, researchers and counselors can use this methodology to predict study outcomes with a binary operationalization like retention or degree attainment and provide advice accordingly (for examples, see Schelfhout, Wille, Fonteyne, Roels, De Fruyt et al., 2021). However, the method does not have to limit itself to education but can also find purpose in work or organizational environments where RIASEC theory originated (Holland, 1997). For instance, LRIF can calculate a personal retention fit for each worker within a specific company. As such, LRIF simultaneously (1) aligns the interests of a worker with the workers that stayed with the company, and (2) differentiates the interests of a worker with the workers that left the company.

Third, the LRIF method enables to (pre) determine E – profiles when doing research on the PE interest fit of individuals with an environment. Indeed, the LRIF method estimates E – profiles through the obtained regression coefficients, a feat that is inherent to all regressed PE interest fit methods in literature (Edwards, 1994; Schelfhout, Wille, et al., 2022). The present study shows that E – profiles obtained through LRIF approximate the E – profiles rendered through averaged incumbent RIASEC scores, while yielding PE interest fit measures with a stronger criterion validity. In such a way, regression fit does not contradict the established incumbent methods, but in fact is an upgraded incumbent method that updates E – profile generation by including variance factors within and between dimensions (Schelfhout, Bassleer, et al., 2022).

On a final note, we were also interested in the conceptual nature of the LRIF effect. Assessing the results of the present study, we consider the stronger criterion validity of the LRIF method as (1) partly an effect of the (logistic) regression method as discussed above and (2) partly an effect of integrating aligning and diverging interest patterns into the E-profiles of programs. Of course, both effects are inherently related, as the regression method generates the E – profiles in the first place.

Limitations, Strengths, and Future Research

We acknowledge that the present study also has limitations. First, our study was conducted in a very specific (open access) higher education environment of students that have already made a choice. Future research therefore needs to focus on the application of LRIF in systems with more strict admission requirements like previous performance or standardized test thresholds that constrain choice irrespective of interest fit. This prospective research should also formally test to which extent LRIF can predict study choice using longitudinal designs, which would allow for stronger claims of causation that the present study cannot make.

Second, although the present study does feature more than thirty, largely independent study program environments, the study does make use of only one dichotomous variable (i.e., study choice). Future studies using LRIF may investigate other important binary outcome variables in higher education like (1) attitudinal outcomes such as satisfaction (Oh et al., 2014) or well-being (van Vianen, 2018), and (2) behavioral outcomes like degree attainment (Tracey et al., 2012). However, these limitations are primarily data constraints, not methodological constraints. Apart from the field of education, further research can deploy the LRIF method in fields of research where the PE fit concept is a prominent research construct, such vocational psychology and organizational behavior (Guan et al., 2021; Jansen & Kristof-Brown, 2006). For the field of

education, we especially advocate studies that use LRIF to proactively guide students towards appropriate study programs.

And third, we acknowledge that the LRIF method has different conceptual foundations (i.e., regression) compared to Euclidean distance and profile correlation (i.e., congruence). Therefore, different foundations may lead to different conclusions regarding PE interest fit. For instance, profile correlation and Euclidean distance measure fit in a more traditional way of similarity: How similar are students to the incumbents of a study program? In contrast, the LRIF method provides a different meaning to PE interest fit: which student profiles lead to a specific study program, while diverging from other programs? Rather than viewing them as competing indicators, we therefore consider these measures as complementary operationalizations first and foremost. Admittedly, we scrutinized these measures more thoroughly in the present study to demonstrate that LRIF adequately models study choice by integrating aligning and diverging interest patterns. The results show that LRIF-generated study program RIASEC profiles successfully predict students' study choices, supporting the validity of the approach.

Conclusion

LRIF models the study choice process by integrating the effects of aligning and diverging interest patterns that lead to a specific study program. LRIF accurately distinguishes students who choose a specific study program from those students who choose another study program, outperforming established, non-regression PE interest fit measures. The resulting PE interest fit measure represents the probability of a student choosing the specific program, based on aligning interests with the program and diverging interests away from other programs. The incumbent LRIF E – profile of the specific program thus integrates these aligning and diverging patterns. We consider that such an LRIF incumbent E – profile contributes to a stronger PE interest fit concept.

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Ethical Considerations

We may not disclose the data and analysis code as stipulated in the approved specific ethical protocol (application number 2016/82, Ethics Committee of the Faculty of Psychology and Educational Sciences, Ghent University).

Informed Consent

Data were collected online. Students had to explicitly accept the general terms and conditions, in which was clearly stated that their personal data could be used for scientific research.

Author Contributions

Stijn Schelfhout: Conceptualization, Methodology, Validation, Formal Analysis, Data Curation, Visualization, Writing – Original Draft, Review & Editing, Supervision. **Mona Bassleer:** Conceptualization, Methodology, Validation, Formal Analysis, Data Curation, Visualization, Writing – Original Draft, Review & Editing. **Wouter Duyck:** Conceptualization, Funding acquisition, Methodology, Writing – Review & Editing, Supervision. **Nicolas Dirix:** Conceptualization, Methodology, Formal Analysis, Writing – Review & Editing, Supervision.

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Supplemental Material

Supplemental material for this article is available online.

Notes

1. Literature also features other methods to establish environment profiles like the O*Net project (Rounds et al., 1999).
2. Except for the study programs Medicine, Dentistry, and Performing and Visual Arts, where students are required to pass an entrance examination, secondary education qualifications are sufficient for admission into a higher education study program. As of 2023-2024, students also have to pass an entrance examination for Veterinary Medicine.

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