The Journal of Experimental Education

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/vjxe20

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To cite this article: Stijn Schelfhout , Bart Wille , Lot Fonteyne , Elisabeth Roels , Filip De Fruyt & Wouter Duyck (2021) From Interest Assessment to Study Orientation: An Empirical Advice Set Engine, The Journal of Experimental Education, 89:1, 169-195, DOI: 10.1080/00220973.2019.1605327

To link to this article: https://doi.org/10.1080/00220973.2019.1605327

Published online: 03 Jun 2019.

THE JOURNAL OF EXPERIMENTAL EDUCATION
2021, VOL. 89, NO. 1, 169–195
https://doi.org/10.1080/00220973.2019.1605327

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Stijn Schelfhout, Bart Wille, Lot Fonteyne, Elisabeth Roels, Filip De Fruyt, and Wouter Duyck

Ghent University, Ghent, Belgium

ABSTRACT

Each student faces the challenge of choosing a study program that matches his or her vocational interest. A good person-environment fit (PE fit) between student and study program influences study success and persistence, prerequisites to obtaining the desired degree. But which criterion should be used when presenting advice sets of study options to orient students toward study programs that match their vocational interests? And how long should such a list of study options be? Moving beyond existing, non-evidence-based approaches, the present study sets out to develop an empirical advice set engine (EASE) to optimize the process of matching future students to fitting study options. Compared to existing, non-evidence-based alternatives, EASE shows a better balance between the number and PE fit of the options presented. EASE may be a promising way to rethink how student PE fit information can be used in student orientation and higher education research.

KEYWORDS

Empirical advice set engine; person-environment fit; RIASEC model; study orientation; vocational interests

A student's vocational interest plays an important role in contemporary higher education. For instance, literature indicates that a good person-environment interest fit (PE fit) between a student and a study program predicts academic achievement and persistence (Allen & Robbins, 2010; Nye, Su, Rounds, & Drasgow, 2012; Rounds & Su, 2014; Tracey & Robbins, 2006; Tracey, Allen, & Robbins, 2012). As both academic achievement and persistence are prerequisites for graduation, students face an important decision when they have to choose a higher education study program in pursuit of the desired degree. Especially in educational set-ups with low admission fees or high scholarships, combined with open access to (nearly) all study programs, the possibilities toward higher education are almost limitless (OECD, 2017). As such, assisting students in their study choice by presenting them with a manageable list of study programs—also called an *advice set*—can provide substantial support. To generate such an advice set for an individual student, two factors need to be balanced. How many study programs should the advice set contain? And how high should the fit quality of the advice set be? Finding a balance between length and fit quality of the advice set would ensure that (prospective) students receive a manageable list of suitable study programs to choose from, while the list of programs still allows for study environment exploration (Holland, 1997). To our knowledge, educational research has not addressed these problems directly. In fact, educational research on the use of vocational interest and PE fit information toward study orientation has been scarce altogether. As a consequence, students,

CONTACT Stijn Schelfhout stijn.schelfhout@ugent.be Faculty of Psychology and Educational Sciences, Department of Experimental Psychology, Ghent University, Henri Dunantlaan 2, Ghent, 9000, Belgium.
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student counselors, and orientation tools often rely on tradition or non-evidence-based rules of thumb when establishing the length of an advice set.

The goal of the present study consists of introducing and exploring an *empirical advice set engine* (EASE). This EASE will generate an advice set of appropriate length and fit quality for each student, based on empirical data of students and study programs. At the base of the model, we will use fine-grained methods to model the transition from a very good PE fit to a very bad one for each student. By establishing a critical point or threshold in the balance between the length and fit quality of the advice set, EASE will generate an advice set for each student. As such, we will explore how well our EASE methodology can balance length and fit quality of advice sets. Indeed, the model used will be refitted for each student, providing us with a measure of internal validation. We will also compare EASE to the more classic approaches using congruence indices, providing criterion validity at the student level (for an overview, see Camp & Chartrand, 1992). This comparison will give us an indication of the extent to which we could improve the quality of study orientation if we were to implement our engine. Finally, as validation of EASE at the program level, we will check to what extent successful students would receive their own study program as part of the EASE-generated advice set of study programs, without inflating the number of choices in this advice set.

The importance of vocational interest in student orientation toward higher education

A definition of vocational interest usually incorporates a number of key features that enable and determine higher education study orientation: direction (or prediction), contextualization (interests have an object), stability, and motivation (Rounds, 1995; Rounds & Su, 2014; Su, Rounds, & Armstrong, 2009). First and foremost, vocational interests robustly predict study choice (Whitney, 1969). Today, the comparison of students' interests to study program environments has become a key element in study orientation. Holland proposed a model of vocational interests that enables such comparisons by using the same typology to represent students and study programs (Astin & Holland, 1961; Holland, 1997). This RIASEC typology takes the form of a clockwise hexagonal pattern containing six interest types or dimensions: realistic, investigative, artistic, social, enterprising, and conventional (Lippa, 1998). After decades of model development and evolution, this base concept still remains highly influential, not in the least in the field of (higher) education (Nauta, 2010).

Second, interests are contextualized and always have an object, such as an activity or an environment (Rounds & Su, 2014). This means that students are interested in activities such as solving equations or translating a conversation or in environments wherein these activities take place, such as study programs (e.g., mathematics or applied linguistics) or future occupations (e.g., mathematics teacher or interpreter). When constructing interest questionnaires for study orientation, this object refers to individual study programs and their respective educational activities. Items and scales probing students' interests in these activities eventually lead to a student-specific-personal-interest (P) profile. Since the inception of the RIASEC model, literature has always harbored a vast set of instruments to determine such a P-profile (ACT, Inc, 2017; Arbona, 2000; Rayman & Atanasoff, 1999; SDS, 2017). For study orientation, such an instrument typically consists of a relatively large number of items covering the spectrum of human study–related behavior. SIMON-I, which was specifically designed for student transition toward a higher education setting, is a recent and validated example of this rich assessment tradition (Fonteyne, Wille, Duyck, & De Fruyt, 2017). Items of this instrument comprise both occupation titles (e.g., *linguist* scored on the artistic scale) and (study-related) activities (e.g., *collecting quantitative and qualitative data* scored on the investigative scale) that one enjoys, to be scored on a dichotomous yes-no scale. The score on these items results in a personal RIASEC profile for each (future) student with (standardized) scores on all six dimensions, ranging from 0 to 100. A set of standardized RIASEC scores from SIMON-I will serve as the baseline from which to develop the EASE methodology in the present study. Apart from our specific study, EASE may, however, just as well be applied to person profiles assessed by any Holland instrument other than SIMON-I.

However, before one can compare a student to a study program, the study program profile has to be described using the same typology as the student's P-profile. Different approaches exist to describe an environment in terms of the RIASEC dimensions using, in contrast to a P-profile, an environment or E-profile. An often-used approach in higher education research relies on the *incumbent method* (Holland, 1997). This method uses the assumption that a specific environment is determined through the people in the environment (Schneider, 1987). In other words, applying this assumption to a higher education setting, a study program is represented through its students. As such, the interest profiles of students occupying a certain study program environment (the so-called incumbents) are used to determine the interest profile of that study program environment. As an example from contemporary educational research, Allen and Robbins (2010) defined study programs in terms of the RIASEC dimensions by averaging out the RIASEC scores of students who demonstrated sufficiently high levels of academic achievement and persistence. By tracking a cohort of college freshmen throughout their study curriculum, Allen and Robbins (2010) showed that students with higher levels of congruence between their personal interests and the study program profiles (as determined through the incumbent method, based on historical data of their predecessors) had a better chance at obtaining their degree in a timely fashion.

This last example illustrates the importance of a third key feature of why vocational interest is so important toward higher education study orientation. Vocational interests are regarded as stable constructs (Low, Yoon, Roberts, & Rounds, 2005; Swanson & Hansen, 1988). Students who have a good match with their study program at the beginning of their higher education are likely to still have a good match when they graduate. This stability enables the possibility of researching the predictive power of vocational interest on study results of new students, based on their vocational interest and on historical results from graduates within a specific study program. For instance, recent meta-analytic research on almost 6,000 academic samples has indicated that vocational interests are moderately correlated to variables indicating performance and persistence (Nye et al., 2012). Results also showed that especially the congruence between a person's vocational interest and his or her environment was of particular importance toward performance and persistence. This meta-analysis corrected historical views that doubted the influence of interests on performance variables because they focused largely on the absolute level of interest-dimension scores rather than on PE fit or congruence (Barrick & Mount, 2005).

The stability feature also enables the validation of study orientation. The attraction-selection-attrition model predicts that over time students will gravitate toward study programs that match their vocational interest (Schneider, 1987). This means that successful and persistent students become excellent incumbents for their (completed) study programs. As such, researchers can analyze existing or new methods of study orientation by investigating to which extent successful and persistent students would be oriented toward their original study choice made years ago. Such criterion validity is usually measured through a *hit rate*, with literature reporting numbers between 32% and 69%, depending on the interest inventory used (Burns, 2014; Donnay, 1997). Each match between a (successful and persistent) student's study program and the advice given through the method of study orientation is considered a hit for that study program. Derived from this hit rate, one could also investigate how many times a program was advised as part of an advice set. This *alternative* rate (or alt rate) for a study program will directly influence the length of an advice set. Indeed, if study programs have higher alt rates, students will receive advice sets with more study programs. However, one has to be careful not to inflate the future student's advice set with too many study programs in order to boost the validity and usability of the instrument. Such an expansion of the advice set could overwhelm the student with options and thus hinder the process of environment exploration. When validating an instrument for study orientation, one should therefore aim at high hit rates for all study programs, while keeping the alt rate for study programs as low as possible. As an example, if the study program *Economics* has a hit rate of 81% with a 25% alt rate, it means that 81% of the students in this study program (Economics) would receive their own study program as a part of their advice set. This also means that 25% of the students inside and outside of Economics would receive this choice as a part of their advice set. In this study, we will explore to which extent the alt rate (in addition to the hit rate) provides extra information toward the validation of study orientation. Since both concepts are measured at study program level, the external validation of our EASE methodology will also be conducted at program level.

As a final characteristic, vocational interest can also act as motivation toward goal attainment, as described in social-cognitive theories of vocational interest (Lent, Brown, & Hackett, 1994; Rounds & Su, 2014). Indeed, interest in certain activities like solving equations or translating texts can (re)direct and energize the student's endeavors toward studying mathematics or applied linguistics, thus, creating a study environment that facilitates focus on obtaining the desired degree. As such, the motivational component can explain why a good fit or match between student and study program leads to academic achievement and persistence.

Fitting students to study programs

Early approaches to determine the PE fit between person (a student) and environment (a study program) profiles have long relied on the comparison of the highest scoring dimensions to obtain a congruence index, also called high point coding (Brown & Gore, 1994; Young, Tokar, & Subich, 1998). In such an index, the letters of the RIASEC dimensions for both P- and E-profiles are ranked from high to low based on the dimension scores. This procedure results in codes that describe students and programs such as SAIRCE or CESAIR. By comparing the rank and placement of the letters in the P- and E-profiles, most often only the first letters (one, two, or three dimensions at best), a categorical or ordinal measure of fit is established. As an example, the Holland congruence index compares the highest dimensions of both P- and E-profiles (Holland, 1963). If these dimensions are the same (e.g., RIASEC versus RSIACE), the match between student and study program is deemed a good fit. Although these classic congruence indices have the advantage of being user friendly and transparent, they also have limitations (Tracey & Robbins, 2006). To give one example, too much emphasis is put on the absolute level of the scores; whereas, the relative magnitude of the interest dimensions remains underused. For instance, both P- (60, 59, 59, 20, 30, 30) and E- (60, 31, 31, 20, 30, 30) profiles would result in an equivalent 3-letter code (RIA) based on classic congruence indexing. However, closer inspection of both profiles reveals substantial differences. The P-profile displays the highest score in the R dimension, with I and A being close seconds. In contrast, the E-profile displays a high R score, with the I, A, E, and C dimensions being at a much lower level. The previous example illustrates another problem. Letter coding does not provide a solution to tied dimensions (De Fruyt, 2002). Indeed, following the example above, the P- and E-profiles could also have been coded RAI, instead of RIA.

As a reaction to these concerns, alternative measures of PE fit have surfaced. One of these methods adopts a continuous approach, expressing the fit between person and environment through a mere correlation between profiles, while still being predictive of study success in the first year of higher education (Tracey et al., 2012). For instance, the PE correlation fit between a profile P (60, 59, 59, 20, 30, 30) and a profile E (60, 31, 31, 20, 30, 30) would amount to $r = .62$. The example clearly shows the difference with the letter-coding approach that coded both profiles as RIA without distinction. Indeed, by using a correlation, the relative magnitude of the dimension scores in both profiles is taken into account. The difference in elevation of the I and A dimensions of the profiles is reflected in a still high but less than perfect correlation coefficient.

This approach has the advantage that it uses the entire profile, while also rendering a continuous measure for additional, more fine-grained analyses.

The correlation approach is also immune to the absolute height of RIASEC dimension scores. Studies have shown that the average elevation of all dimensions does not have a direct effect on whether or not people want to engage in a certain occupation or activity (Prediger, 1998). However, literature also indicates that within lower elevated profiles the link between PE fit and results is even stronger (Darcy & Tracey, 2003; Tracey & Robbins, 2006). As such, study orientation should not focus on the height of the dimensions but on PE fit between profiles to avoid disadvantaging students with a low profile elevation. To address this problem, PE correlation fit seems a good solution. Finally, in addition to these advantages, the correlation index of PE fit is still easy to compute and interpret (from −1, being the worst fit possible, to +1, being a perfect fit) without much prior intensive data processing.

Translating PE fit information into study orientation advice

Despite the obvious theoretical and empirical advantages, questions remain regarding the practical implementation of this correlation approach to PE fit. Specifically, in a concrete study orientation situation, this approach generates a series of correlations between a student's interest profile and a set of available study options, reflecting the transition from a very good PE fit to a very bad one. Until now, we have no answer to the question concerning how good the PE fit between a student and a study program has to be before the program should be recommended to that specific student. This lack of a theoretically or empirically based objective criterion delineates a problem that the more classic congruence indices (see above) also could not solve. Indeed, educational literature has remained indecisive and vague concerning how the translation from PE fit to study orientation should be conceived. First, literature displays a multitude of congruence indices, all proposing different rules to indicate (the degree of) PE fit, each with its own (dis)advantages. As a result, what is deemed *a good fit* is only valid within the confines of one specific index (Brown & Gore, 1994; Camp & Chartrand, 1992; Young et al., 1998); for instance, the dichotomous Holland index defines a good fit as a match between the highest dimensions (Holland, 1963). Second, none of these indices provides an answer to the question concerning how good *exactly* the PE fit between a student and a study program has to be before the program can be advised to that specific student. In other words, there is no objective and uniform criterion based on theory or empirical data that allows for making a distinction between a sufficient fit and an insufficient one. For instance, in the dichotomous Holland index, described above, is it sufficient that only the highest dimensions match in order to include it in the advice set? Or do the second and third highest dimensions also need to match between student and program? As a result, contemporary study orientation still has to rely on mere tradition or suboptimal, non-evidence-based rules of thumb to guide students toward fitting study programs.

Present study

How high does the fit between a student's interests and an available study program have to be to take this program into consideration as a potential study option, especially when comparing this fit to that of other study programs? To our knowledge, this question has not been researched in educational literature. Since there is no evidence-based criterion, the ideal length of a possible advice set featuring sufficiently high-fitting study programs also remains unknown. The objective of the present study is to answer both issues by balancing them against each other. As such, we will introduce and explore EASE, an *Empirical Advice Set Engine*. At its core, EASE optimizes the process of translating correlation PE fit information into concrete study advice, using an empirically fueled engine as a base for student friendly applications. Such a translation should always result in a balanced list of suggested study programs toward environment exploration, while containing only study programs that match a specific student's interests to a sufficient degree. To enable this translation, we will use a fine-grained continuous method of PE correlation fit between a specific student and a list of available study programs, effectively modeling the transition from programs with a very bad PE fit, to programs with a very good PE fit. By building on this transition modeling, EASE will dispense a custom-made advice set of study options to each future student individually, while taking into account the correlation fit between the student's profile and the entire pool of available study options. As such, the criterion for this advice set will take the form of a minimal fit quality or threshold, relative to the available options. Study options that demonstrate a level of fit surpassing this threshold are included in the advice set, while the remainder of the study options is excluded, so that they do not have to be explored or processed by the student.

It is important to note that the decision to (not) include any given program in the advice set is always made relative to the pool of other possible study programs. As study orientation eventually leads to making a choice of study program, it is only fair that all possible choices be compared against the other choices. Ultimately, the proposed procedure should serve as the baseline for data-driven applications, while strengthening the quality and validity in establishing appropriate advice sets of study options for prospective higher education students. To this extent, the present study will explore three main research questions.

For the first question, we will test how well the novel method succeeds in balancing advice set length and fit quality for each student by using two large data sets containing student-interest measures. The first data set provides us with a large sample of real-life, successful students from various study fields, used to estimate study program interest profiles. The second data set provides us with a sample of future students seeking actual orientation toward fitting study options. As such we will test the following hypothesis (H),

H_1: *EASE manages to balance the length and fit quality of student advice sets.*

Since the balance between student's advice-set length and PE fit quality is a key feature of this study, we will also compare EASE to advice sets generated by classic congruence indices, such as the Holland index, discussed above, providing criterion validity at the student level.

H_2: *EASE displays a better balance between student advice-set length and fit quality than classic congruence indices.*

Finally, we will test the validity of the EASE methodology at the program level by exploring how many persistent and successful students would receive their own study program as part of their advice set. We also deem it worth investigating whether receiving the correct study program as part of the advice set does not needlessly inflate the length of the advice set. We will thus compare the EASE-generated advice sets to those generated through classic indices.

H_3: *EASE generated advice sets have higher validity than those generated by classic congruence indices by displaying a better balance between hit rate and alt rate.*

Method

Data sets

All data were primarily gathered in function of a large, university-wide longitudinal project to enhance study orientation and study success among (future) students at a western-European university (Shanghai Top 100) with 11 diverse faculties. From this project, two obtained data sets were used, D_1 ($N_1 = 4{,}892$; 66% female) and D_2 ($N_2 = 7{,}063$; 61% female). D_1 features the scores on the RIASEC questionnaire SIMON-I (Fonteyne et al., 2017) from third bachelor's and master's

Table 1. Balance between PE fit Quality and Number of Possible Study Options.

Fit quality	Options	Balance
−0.87	62	−54.1
−0.85	61	−52.09
−0.83	60	−49.61
…	…	…
0.22	28	6.1
0.26	27	6.95
0.26	26	6.8
0.32	25	7.92
0.37	24	8.9
0.39	23	8.87
0.49	22	10.74
0.5	21	10.58
0.51	20	10.18
0.54	19	10.21
0.58	18	10.49
0.59	17	9.97
0.64	16	10.26
0.68	15	10.16
0.7	14	9.79
0.72	13	9.39
0.77	12	9.26
0.79	11	8.71
0.82	10	8.16
0.84	9	7.58
0.9	8	7.17
0,90	7	6.31
0.91	6	5.46
0.92	5	4.62
0.96	4	3.86
0.98	3	2.94
0.98	2	1.96
0.99	1	0.99

students, assessed in the period between August 2013 and September 2015. Students were recruited from 62 study programs with on average 78 students for each program and a wide variety in student numbers ($SD = 80.20$). These students all met the conditions of academic success and perseverance by completing the first two years of their study program (see Allen & Robbins, 2010). Only students who indicated that they would consider choosing the same study program again were included (97%). For each study program, the scores of all successful students, or *incumbents*, were averaged out, following the procedure of Allen and Robbins (2010). This operation provides us with an E-profile for each of the 62 study programs. These programs and their E-profile will function as possible study options for the current investigation. D_2 contains the RIASEC interest scores of future students (ages 16–18 years) on the verge of making the transition into higher education. Interest assessments were conducted using a freely available, online version of SIMON-I in the period between January 2014 and September 2015 (see Appendix A). Highly irregular (for instance, scores of 0 and 100 on all dimensions) and incomplete profiles were excluded from the analyses (2%). All entries were rescaled analogous to D_1. There was no overlap between D_1 and D_2.

Procedures

EASE

Using the P-profiles of 7,063 future students and the E-profiles of 62 study programs, we will apply the EASE methodology to each student individually. As we are looking for a way to model the transition from a very good PE fit to a very bad one for each student, we have to correlate

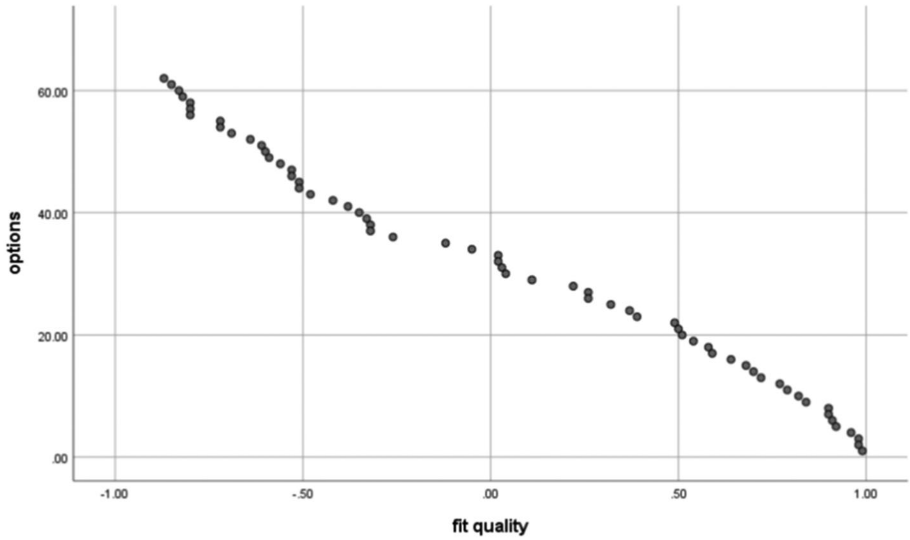

Figure 1. Scatterplot of options and fit quality for a random student.

the student RIASEC profile (six dimensions) with each of the 62 study program RIASEC profiles (the same six dimensions). Such a correlation is a measure of PE *fit quality*. Table 1 shows an example for a single random student, ranking the fit quality of the student with the available study options from high to low. Each study option with a specific fit quality for an individual student is tied to a number of possible study options. This *options* variable indicates how big the advice set of the student would be, if the corresponding fit quality would act as the threshold (including all programs at or above its fit quality value) for making the advice set. Exploring the relation between the (PE) fit quality and the number of options for this student even further, we observe a linear trend between the two variables. This trend indicates that the distribution of fit quality within one student could approximate a uniform distribution, resulting in a gradual transition from very-good-fitting to very-bad-fitting study options. We will test this approximation toward a uniform distribution for each student. Moreover, a high fit quality is tied to a low number of options and vice versa (Figure 1). This fit quality/options combination reflects the *balance* between the length and the minimal fit quality of the possible advice set for each student, formally defined as

$$balance = fit\ \ quality\ \times\ options \tag{1}$$

Balance has a single purpose: By finding the best possible balance for a student, we will be able to determine the optimal threshold for that student, weighing the number of study options against the minimal fit quality for study options in the advice set. As such, study options with a PE fit equal to or above this threshold will make up the proposed advice set.

To find this optimal threshold, we introduce EASE. Its purpose will consist of finding the optimal threshold for each student separately, based on the balance variable. Further inspection of Table 1 shows that the balance variable rises to more than 10 and then goes down again. In other words, it displays the larger part of a symmetrical and inverted, U-shaped curve, with the turnover point (the point at which the rise stops and the descent begins) somewhere near the 10-point mark of the balance variable. This turnover point is the equivalent of the *vertex* of a parabola and corresponds to our intended threshold. In other words, the vertex represents the point of ideal balance between a sufficient PE fit and an acceptable length of the advice set. If we can connect the vertex to the corresponding fit-quality value, we have our threshold value for the advice-set makeup. As we are looking for a PE correlation fit quality, and the balance variable displays an inverted U-shaped curve, we propose a quadratic linear regression of fit quality on balance using the functional form of a parabola,

$$balance \sim a \times fit\ quality^2 + b \times fit\ quality + c + e \tag{2}$$

to model the balance curve. As such, parameters a, b, and c need to be estimated and e represents the residual variance. Expressing fit quality as a function of balance allows us to estimate the x-coordinate of the vertex through its parameters by using

$$vertex = -\frac{b}{2a} = optimal\ correlation\ threshold \tag{3}$$

and to obtain our optimal correlation threshold to reflect the ideal balance between length and fit quality of the advice set. All options above the computed optimal threshold are deemed of good enough fit quality and they will be included in the optimal and student-specific advice set. However, as the parabola is estimated through a regression, there will always be a margin of error. This margin of error could result in inflated or deflated thresholds, illegitimately discarding or including study options to form the advice set. Considering we are advocating the principle of self-directed search, we deem it more important to keep borderline valid options in the advice set rather than discarding the less valid ones. To ensure that EASE does not discard these valid options, we establish the actual threshold at the lower end of the threshold's confidence interval. Because the optimal threshold is based on parameter estimations, we use parameter confidence intervals (CI) to establish its own CI. In doing so, we take a conservative approach and use the upper and lower parameter bounds rendering the widest interval. Finally, the explained variance (R^2) of the quadratic regression provides us with a measure of how well the model fits the data. In other words, the EASE model fit will provide us with an estimate of how well the EASE methodology managed to balance advice-set length and fit quality for a specific student. In sum, we define EASE as a quadratic linear regression, fueled by the model of a very good PE fit to a very bad PE fit between a student and a set of possible study programs, enabling the construction of an actual threshold for each student, which ultimately results in a balanced advice set of appropriate length and sufficient PE fit for each (future) student. In order for EASE to work, we do make the assumption that the PE fit values between a student and a pool of study programs entirely cover the correlation continuum. This assumption has to be tested.

Congruence indices comparisons

As a test of the last two hypotheses, the EASE-generated advice sets of study programs for each student are compared with more-classic methods of constructing advice sets based on congruence indices, such as the letter-congruency index discussed above. As these congruence indices all have specific features, we chose to include three classic indices, adapted or combined from the dichotomous one-letter agreement index (Holland, 1963) and the two-letter agreement index (Healy & Mourton, 1983).

For the first comparison (H_2), the EASE data and letter-method data are acquired from D_1 and D_2. For the EASE data, the procedure is identical to the one described above. For the congruence indices using letter methods—that is, *1 L,* (one-letter), *2 L* (two-letter), and *1 + 2 L* (one- and two-letter combination—the procedure for making advice sets is conducted as follows. Study programs are included in the 1 L advice set if the future student and study option profiles have the same highest scoring RIASEC dimension. For instance, a study program with E-profile code ECISAR (e.g., economics) would be included in the advice set of a student with P-profile ERCIAS. Study programs are included in the 2 L advice set if the two highest dimensions from the study-program profile reoccur in the three highest dimensions from the future student profile. For instance, a study program with E-profile code ECISAR (like economics) would be included

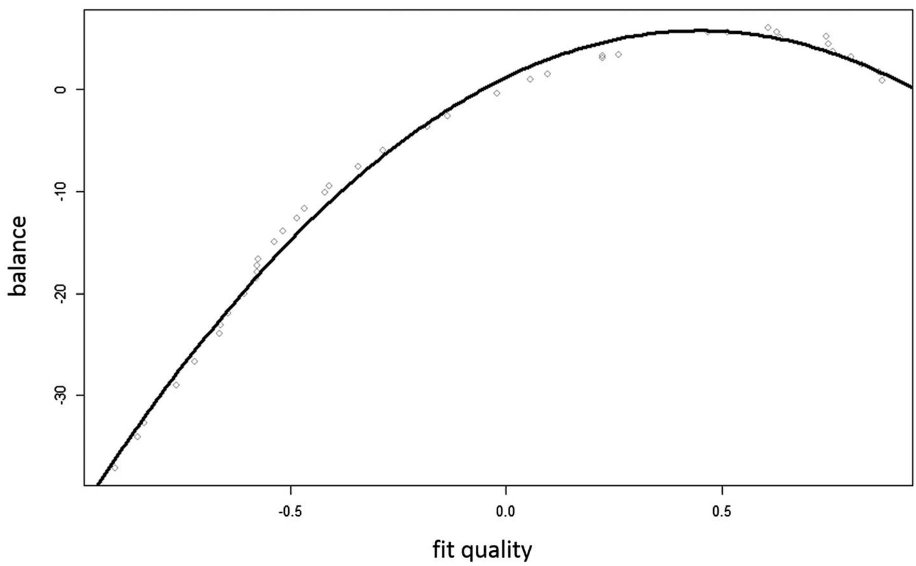

Figure 2. EASE regression for a random student. Scatter plot data points are depicted in hollow. The quadratic regression is drawn in full.

in the advice set of a student with P-profile ERCIAS. Study programs are included in the 1 + 2 L advice set if the conditions of 1 L or 2 L are met.

For the second comparison (H_3), the data is acquired from D_1 (successful and persistent students) and the procedure for both the EASE application and the letter methods is identical to the procedure from the first comparison with one exception: The profiles of the (successful and persistent) students are also drawn from D_1.

Measures and analyses

PE fit distribution

Before we apply EASE to the data, we have to verify to which extent the PE fit distribution for each student and the pool of study options approximates a uniform distribution. A good approximation indicates a gradual coverage of the correlation continuum, with a linear transition from very good fitting to very bad fitting study options. The approximation is measured through an R^2 as the result of a regression of options on fit quality (or vice versa).

EASE application

Figure 2 gives an example of an EASE application for a random student. As the regression of the parabola model has to be carried out for each of the 7,063 students, analyses will report the range, mean, and standard deviation across all students of the following variables: linear fit (R^2) (measuring how well the engine manages to balance the length and fit quality of the engine), the optimal and actual correlation threshold and the advice-set size and average fit quality.

EASE application versus classical 1L, 2L, and 1 + 2 L methods

Two comparisons are made: (a) the balance between average advice-set size and fit quality of both methods at the student level (H_2) and (b) the balance between the hit rate and alt rate of study programs (H_3). To control for the substantial differences in student numbers across study programs (see above), we use percentages (instead of absolute numbers) to ensure each study

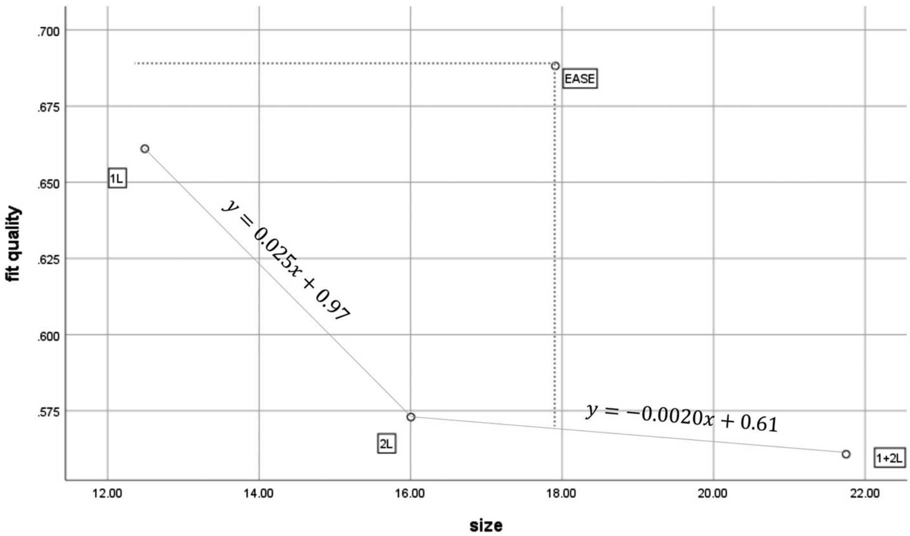

Figure 3. Projection of EASE onto the letter-method interpolation of the relation between size and fit quality of student advice sets.

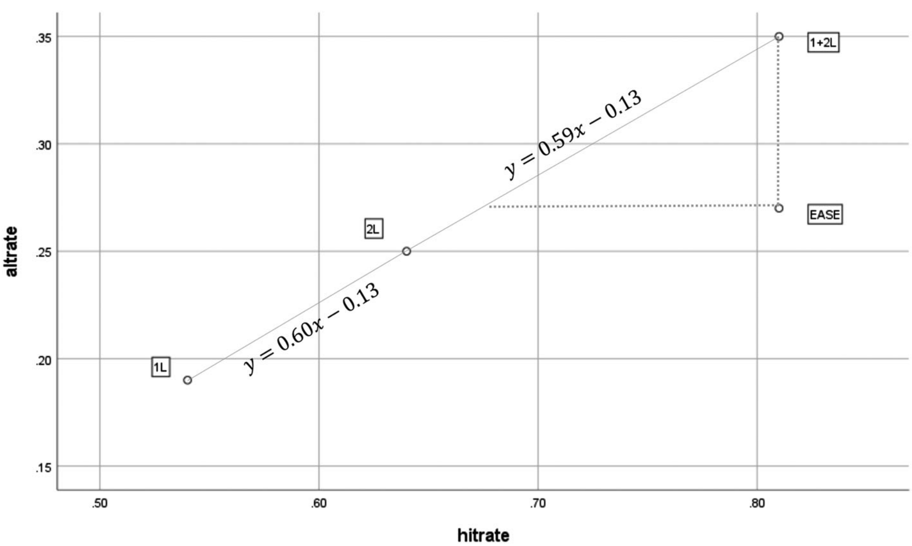

Figure 4. Projection of EASE onto the letter-method interpolation of the relation between hit rate and alt rate.

program has the same weight. For each comparison, EASE results will be projected onto an interpolation of the results from the classic congruence indices (i.e., 1 L, 2 L, and 1 + 2 L methods). As such, Figure 3 and Figure 4 show two polynomial interpolations, each consisting of two linear equations (depicted in full). These linear equations connect the results from 1 L with 2 L and 2 L with 1 + 2 L. Figure 3 depicts the relation between advice-set size and fit quality of a student advice set. A congruence index method with a lower advice-set fit quality is tied to a higher advice-set size: Students receive more study programs in their advice set, which consequentially fit worse. Figure 4 shows the relation between hit rate and alt rate of study programs. A congruence index method with a higher hit rate is tied to a higher alt rate. In other words, increasing the number of options each student receives (alt rate) increases the chances that the student will also receive his or her own program as a part of the advice set (hit rate). By projecting the EASE

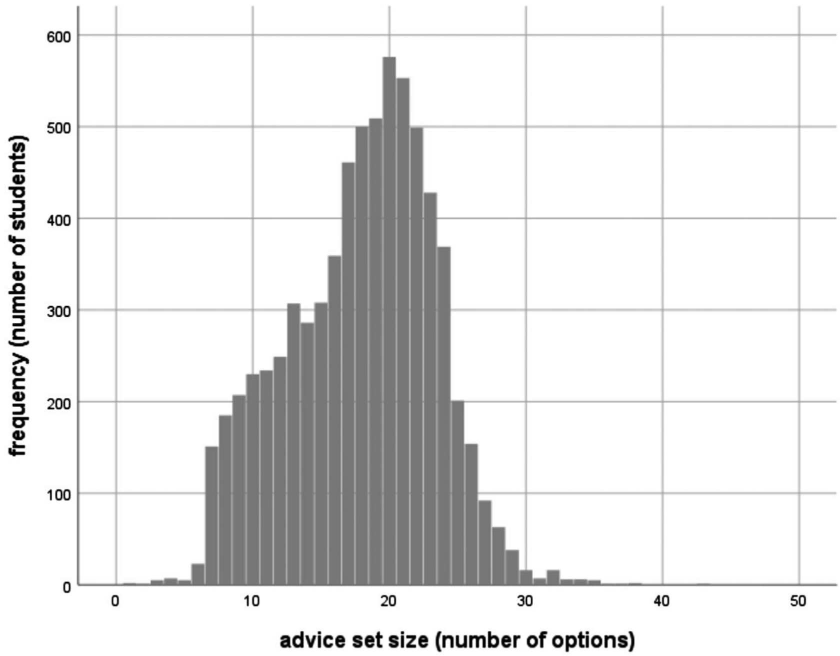

Figure 5. Distribution of advice-set size.

results onto the interpolation of the classic methods (dotted line), hypothetical values can be established. We can now use a two-sided, one sample *t* test to determine whether these hypothetical values significantly differ from the observed EASE values to investigate whether EASE (versus classic congruence indices) indeed manages to obtain a better balance between the size and fit quality of a student advice set and the hit rate and the alt rate, respectively, of study programs. For an interpretation of the average differences, we will also report a Cohen's *d* effect size, with 0.01 = very small effect, 0.20 = small effect, 0.50 = medium effect, 0.80 = large effect, 1.20 = very large effect, 2.00 = huge effect (Sawilowsky, 2009).

Results

PE fit distribution

Results shown in Figure 1 already hinted that the transition of PE fit within a student from a very good fitting study program to a very bad one is a gradual and continuous process, following a uniform distribution. Formally, we tested this assumption for each prospective student, with an average regression R^2 across students of .97 (SD = .03) and a range from .84 to .99.

Hypothesis 1

Our first aim was to test how well EASE would be able to balance advice set length and fit quality. Our EASE methodology proved to be well capable of balancing advice set length and fit quality, as indicated by high levels of explained variance. Indeed, the quadratic regression of balance on fit quality resulted in a linear fit with an average R^2 of .99 (SD = .01) ranging from .86 to .99 across the (prospective) student sample. This high level of explained variance resulted in an accurate estimation of the optimal correlation threshold, which ranged from r = .14 to r = .58 (M = .46, SD = .06). The subsequent actual threshold ranged from r = .11 to r = .53 (M = .44,

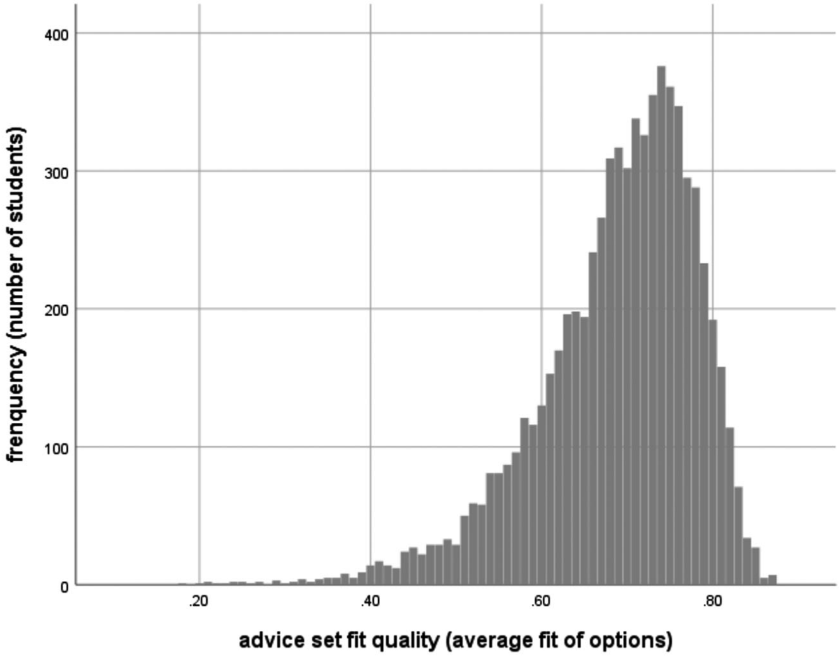

Figure 6. Distribution of advice-set fit quality (based on correlations between the P- and E- RIASEC profiles).

SD = .06). The width of its confidence interval ranged from .02 to .15 (*M* = .06, *SD* = .02). The advice sets were constructed based on the actual threshold for each prospective student separately. Figure 5 shows the distribution of the student advice set sizes. A student thus received an average advice set of almost 18 study options (*M* = 17.91, *SD* = 5.37), which is about 29% of the complete pool of 62 study options. Also, about 98% of the students received an advice set ranging from seven to 28 options. Figure 6 shows the distribution of the (average) fit quality of the student advice sets. The fit quality of study options in an advice set was on average very high, with *M* = .69 (*SD* = .09) and a range in a right-skewed distribution from *r* = .18 to *r* = .87. Also, about 96% of the students had an advice set with an average fit quality of *r* = .50 or better. There were no advice sets with zero options. This means that all students received at least one possible study option as part of their advice set. Considering the combined results of the analyses regarding our first hypothesis, we decide to accept H_1.

Comparing EASE and congruence indices

Hypothesis 2

Our second aim was to establish whether EASE displays a better balance between advice set size and fit quality than the classical approaches. Figure 3 clearly indicates that EASE results are above the interpolation line of the classic congruence indices. This deviation from the interpolation line already suggests that EASE manages to balance student study advice-set size and program-fit quality better than the classic congruence indices. By projecting the EASE values onto the interpolation line we can obtain hypothetical values to formally test the difference between EASE and the interpolation of the classic congruence indices on both advice-set size and fit quality. Note that the congruence indices dispensed a varying number of zero-sized advice sets (i.e., students who would receive no valid options). The 1 L, 2 L, and 1 + 2 L methods rendered 401 (6%), 22 (<1%), and 3 (<1%), respectively, of such zero-sized advice sets.[1] Average fit-quality values were computed by excluding the results of zero-sized advice sets.

EASE-generated student advice sets display an average size of 17.91 options. Inserting this value into the interpolation projects an average student advice set fit quality of $r = .57$. This is the fit quality that the classical letter methods would generate for an advice set size of 17.91. However, EASE generated student advice sets with a much better average fit quality of $r = .69$, compared to the interpolated $r = .57$. We can test this difference by using a two-sided, one sample t test. The difference between the observed EASE value and the projected interpolation value proved to be significant, $t(7062) = 106.54$, $p < .001$, Cohen's $d = 1.27$. This means that an equal advice-set size for EASE and the classic congruence indices results in a very large difference in advice-set fit quality, with EASE scoring $r = .12$ above the level of the interpolation line. Also, EASE-generated advice sets display an average explained variance of 48% (i.e., $.69^2$), while the classic congruence indices predict an explained variance of only 32% ($.57^2$). In other words, EASE explains 16% more variance concerning the relation between a student's P-profile and his or her advice set of study programs (E-profiles) compared to the interpolation of the classic congruence indices (at equal advice set size).

By keeping advice-set size constant, EASE yields better fit quality. It is also possible to reverse this rationale: Does EASE generate larger advice sets while still keeping a constant fit quality? EASE-generated student advice sets display an average fit quality of $r = .69$. Inserting this into the interpolation equation yields a projection that is off the chart. As such, we propose to take a conservative approach and adopt the 1 L edge value of 12.49 (advice-set size) as an overestimation of the EASE-projected value, as the actual interpolation would result in an even smaller-sized advice set. However, EASE generated advice sets with a size of 17.91 options, compared to the interpolated 12.49. A two-sided, one sample t test revealed a significant difference between this EASE advice-set size and the conservative projection on the interpolation line, $t(7062) = 84.79$, $p < .001$, Cohen's $d = 1.01$. This means that EASE can maintain the same (maximal 1 L) fit as the classic congruence indices, while rendering larger advice-set sizes, with a difference of about 5.42 options. In sum, the tested projections of EASE on the interpolation line of the classic congruence methods indicate that EASE manages to outperform these classic methods in balancing advice-set size and fit quality. As a consequence, we decide to accept H_2.

Hypothesis 3

Our third aim was a test of the validity of the advice sets at the level of the study program. We investigated whether successful students received their own study program more often by using EASE over classic congruence indices through a higher hit rate, without inflating the advice set through a higher alt rate. Figure 4 clearly indicates that the EASE results are below the interpolation line of the classic congruence indices. The deviation from the interpolation line already suggests that EASE will have a higher hit rate at a lower alt rate. To formally test the difference between the classic congruence indices and the EASE methodology, we projected the observed EASE values onto the interpolation line of the classic congruence indices to obtain hypothetical values.

Through the EASE method, study programs receive an average hit rate of .81. Projecting this .81 onto the interpolation line of the classic congruence indices renders an alt rate of .35. However, EASE displays an alt rate of .27. A two-sided, one-sample t test revealed that EASE has indeed a lower alt rate than the interpolation line, $t(61) = -6.04$, $p < .001$, Cohen's $d = 0.77$. This means that an equal hit rate of .81 for both EASE and the classic congruence indices results in a large difference in alt rate, with EASE scoring .08 lower than the classic congruence indices. In other words, EASE improves (lowers) the alt rate of study programs with 23% compared to the classic congruence indices at an equal hit rate of .81. In sum, through the use of EASE, programs have to appear less often in an advice set to achieve the same hit rate.

We can also reverse this rationale, analogous to Hypothesis 3. What happens with the hit rate if we keep the alt rate constant? The EASE method generates an average alt rate in study programs of .27. Projecting this alt rate onto the interpolation line renders a hit rate of .68. EASE, however, displays a hit rate of .81. A two-sided, one-sample t test revealed that EASE has indeed a lower alt rate than the interpolation line, $t(61) = 8.82$, $p < .001$, Cohen's $d = 1.12$. This means that an equal alt rate of .27 for both EASE and the classic congruence indices results in a very large difference in hit rate, with EASE scoring .13 higher than the classic congruence indices. In other words, EASE improves (strengthens) the hit rate of study programs with 19% compared to the classic congruence indices, at an equal alt rate of .27. In other words, if one would present study programs equally often in study advice through both methods, EASE will yield a higher hit rate than classical methods. To summarize, the tested projections of EASE on the interpolation line of the classic congruence methods indicate that EASE manages to outperform these classic methods in validity by demonstrating a better balance between hit rate and alt rate of study programs. As a consequence, we decide to accept H_3.

Discussion

Assisting (prospective) students in their study choice by orienting them toward a set of study programs that really matches their interests is of great importance for enhancing study success and persistence in higher education (Allen & Robbins, 2010; Nye et al., 2012; Rounds & Su, 2014; Tracey et al., 2012; Tracey & Robbins, 2006). Until now, educational research remained indecisive and vague regarding how to translate PE fit into study advice. In the past, students, scholars, and counselors relied on non-evidence-based rules of thumb and a plethora of congruence indices, each with its own flaws and strengths, to establish goodness of fit (Brown & Gore, 1994; Camp & Chartrand, 1992; Healy & Mourton, 1983; Holland, 1963; Nye et al., 2012; Young et al., 1998). Also, an objective criterion had not emerged for deciding how well exactly a student's interests had to match a study program in order for the program to be eligible to be part of the advice set of study programs presented to the student. As a consequence, the ideal length of such a custom-made advice set also remained unknown. This is quite surprising as vocational interest and PE fit are of capital importance to higher education study orientation, as we have argued, through the features of prediction, contextualization, stability, and motivation (Lent et al., 1994; Low et al., 2005; Nauta, 2010; Rounds, 1995; Rounds & Su, 2014; Swanson & Hansen, 1988; Su et al., 2009; Whitney, 1969). To translate PE fit into study advice, the present study proposes the EASE (empirical advice set engine) methodology. EASE empirically generates an individualized advice set of study programs that is sufficiently large and of good fit quality for students. In doing so, the engine balances the number of study programs in the advice set versus the minimal fit quality required for such a study program to enter the advice set. EASE uses the benefits of the fine-grained PE correlation fit measure to model the transition from a very good PE fit to a very bad PE fit between any given student and a set of study options (Allen & Robbins, 2010; Tracey et al., 2012). By finding the ideal balance between the number of study options and minimal PE fit, a correlation threshold is generated for each student. Study programs with a PE fit (regarding the specific student) above the threshold are added to the advice set and presented to the student as part of the final advice set, while the other options are no longer taken into account as programs fitting the student's interests.

To explore the possibilities of our EASE methodology, we presented three research questions. (1) How well does the EASE methodology succeed in balancing the length and fit quality of a student advice set? (2) How do the EASE-generated advice sets compare to sets generated with more traditional congruence (letter) indices? (3) How valid is the EASE methodology?

To answer to the first question, EASE displays a remarkable ability to balance length and fit quality of student advice sets by determining an empirical PE-fit threshold for each student, through the use of the parabola model. This threshold leads to varied student advice sets of about 18 study programs, with about 98% of the prospective students receiving an advice set between seven and 28 choices, leaving ample room for study environment exploration (Holland, 1997; Gottfredson & Holland, 1975). Our study also includes a number of validation mechanisms for the parabola model. Indeed, the model fits to all student profiles individually, while also providing two forms of criterion validity, at the student level and the study program level, addressed in research questions two and three, respectively.

To answer the second question, EASE presents student advice sets that are qualitatively better than those generated with the classical congruence indices. For instance, an EASE advice set of about 18 study programs delivers study advice to future students that explains 48% of the variance in the relation between the student's P-profile and the advice set of study programs. This variance level is 16% higher than the level achieved by the classic congruence indices. Also, about 98% of all students received an advice set with a fit quality of $r = .50$ or better.

Finally, to answer to the third question, our EASE methodology shows strong criterion validity for study programs; about 81% of all successful students received their own study choice as part of their EASE-generated advice set. Comparing the EASE hit rate to the range reported in literature (i.e., 32% to 69%), our method seems to be more accurate than using classic methods of making the PE fit (Burns, 2014; Donnay, 1997). Moreover, EASE also outperforms a combination of congruence indices by displaying a hit rate that is 19% higher at equal alt rates (Holland, 1963; Healy & Mourton, 1983). The results from this last question also show the incremental research value of the alt rate when validating study-orientation tools. Certainly, high hit rates in study orientation are important to ensure validity but not at all cost. Good study orientation should also monitor whether the alt rates are needlessly inflating the student's advice set: if too many less fitting programs are suggested, the process of environment exploration will suffer (Holland, 1997; Gottfredson & Holland, 1975). Classic congruence indices may present a strong hit rate or a low alt rate. But EASE offers a better balance between the two, with an alt rate that is 23% lower than those of the classic congruence indices, measured at equal hit rates. As such, EASE presents the right programs to the right students, without having to present programs too often to achieve that.

In sum, the exploration of our three research questions clearly shows that the classical congruence indices still produce acceptable results concerning fit quality and validity of the generated advice sets to orient students toward higher education. However, when comparing these results to those obtained through the EASE methodology, we see that EASE provides students individually with better fitting and valid study options. In addition to better quality and validity of the advice set, the EASE methodology also presents a number of positive features that the congruence indices fail to reproduce. Indeed, when generating advice sets for future students, EASE ensures an orientation advice set of at least one study option for each student, while the congruence indices cannot provide orientation for up to 6% (i.e., the number of zero-sized advice sets for the 1 L method) of all future students. As such, EASE has a better answer (versus the classic methods) to the absence of programs with a dominant C dimension. Next, EASE succeeds in establishing an objective, data-driven, and student-specific criterion that enables the identification of study programs that should be part of the student specific advice-set orientation (versus study programs that should be discarded). Finally, EASE establishes this criterion while comparing all available study programs against each other. This comparison seems only fair when considering that study orientation should ultimately lead to making a choice between study programs.

Theoretical implications

We established, as an important theoretical addition to the structure of PE fit, that the transition from a very good PE fit to a very bad PE fit is apparently a very gradual and continuous process for each student. The correlation approach thus provides a continuous, fine-grained measure for modeling the structure of PE fit as an approximated uniform distribution. This also means that the parabola estimated for each student has properties that find their origin in the uniform distribution of PE fit. Though these properties were not intended as such, they are a direct consequence of the empirically observed PE-fit distribution and they will influence the length and quality of the advice set. For instance, EASE uses the symmetry about the parabola vertex to distinguish between programs that are suitable for the student and program that are not. Moreover, this distinction is made more clear-cut as the programs are gradually distributed across the course of the parabola. However, EASE does not use the full course of the parabola. Indeed, EASE does not aim for advice sets equal in length for everyone. Instead, each student should receive a list of options based on the fit of his or her profile to the pool of available programs. By using only a part of the parabola course including the vertex, EASE also succeeds in balancing the number of suggested options. As such, EASE renders advice sets of study options that are large enough for the intended self-exploration, without inflating the advice sets to unworkable lengths.

Moreover, this research does not have to limit itself to the domain of education. We speculate that the structural uniform distribution of PE fit as shown in this study could also be present in other settings such as work or hobbies, effectively paving the way for the introduction of EASE in these settings. As such, we advocate further research on the distribution of PE fit between a student and study programs. We also advise researchers to explore this uniform distribution when using the EASE methodology.

Practical implications and limitations

The analyses above show that EASE offers a good method to offer prospective students a list of suggested programs that is not too short or too long and that fits the student's interests well. The practical implications for study orientation toward higher education of the proposed methodology are tied to a number of boundary conditions that deserve further attention. A first and obvious requirement is that there are interest profiles of both (future) students and study programs. Although in the present study these two types of profiles resulted from the same interest instrument (i.e., SIMON-I, Fonteyne et al., 2017), which was administered to future students and to successful students, this is not essential. The only prerequisite is that both personal and environmental profiles are commensurate measures, consisting of the same number of conceptually related (e.g., RIASEC) dimensions making it both mathematically possible and conceptually reasonable to compute the correlations between the two profiles as a commensurate assessment. It should be clear from this study that these correlations form the basis of the EASE method. Any assessment can make use of the EASE methodology as long as the compared measures of person and environment are commensurate.

A second requirement consists of a sufficiently large pool of study options. The present exploration already showed that a set of 62 options is sufficient to extract a very stable advice set. The high amounts of explained variance in the EASE application do seem to suggest that even a smaller pool of study options could enable the balancing of advice set length and fit quality. The question remains—how small can the pool of study options become while still keeping the PE correlation fit continuum sufficiently covered? This needs to be clarified in future research that at the same time asks whether such a small pool needs an advice set to begin with.

A third requirement is a (set of) student RIASEC profiles to apply EASE and generate advice sets. For individual student orientation, the data of a single future student is sufficient to construct a distribution pattern and apply our EASE to that specific student generating a valid and precise advice set, containing an appropriate and sufficient number of study programs.

A final requirement consists of fueling EASE with data. In this exploration, we have provided one possible configuration, defining balance as the (simple) product of options and fit quality in order to pinpoint a correlation threshold. Other set-ups might require adaptations such as weighting the components, if one or the other would be more important in a specific context.

Future research and applications

EASE has the potential to fuel an orientation tool for centers of higher education such as colleges and universities that offer an extensive set of (diverse) study programs. Automating this engine through an online application could reach a vast number of (future) students who could fill out any RIASEC questionnaire. This would enable the entire EASE procedure by meeting the mentioned requirements. By featuring any RIASEC questionnaire, data can be gathered on the profiles of both actual and future students. Actual students could act as incumbents, effectively rendering study program profiles, while the profiles of future students were being run through the engine to generate appropriate advice sets concerning study choice. Advice sets can take a form similar to that shown in Table 1, listing appropriate programs instead of a number of options, including the PE fit through a fit quality for purposes of further exploring the advice set. We also refer to Appendix B, contains a full example for one student, featuring both the EASE execution code and practical application of the algorithm.

Results from the current set of analyses already suggest that the presented EASE methodology has the potential to significantly advance our understanding of the concept of PE fit and how it can be applied in practice. As such, it would also be highly beneficial to use these data from automated online applications to facilitate this process of ongoing research. Indeed, additional research on this method is desired, especially on the properties of EASE across different instruments and contexts. A correlation fit can be used independent of the featured instrument as long as it is possible to establish a correlation between a profile P and E. In theory, this makes our method appropriate for SIMON-I, UNIACT, Self-Directed Search, or any other Holland-based instrument as long as it features all six RIASEC scales (ACT, 2017; Arbona, 2000; Fonteyne et al., 2017; Gottfredson & Holland, 1991; Nauta, 2010; Rayman & Atanasoff, 1999; SDS, 2017). It is worthwhile to compare these instruments regarding variables such as fit quality and advice set size.

Similarly, EASE offers the ability to explore to what extent and under which form the EASE method can be applied to contexts other than education. For instance, given the centrality of interests in many aspects of professional career development, we deem it worthwhile to examine to what extent this threshold method may also be applied in actual working contexts. The EASE method could help in generating advice sets consisting of job profiles, which could then be linked (e.g., by labor agencies) to the interest profiles of individual job seekers.

Conclusion

Person-environment interest fit is an important predictor of higher education performance and persistence. Nevertheless, little progress has been made in charting student PE fit distribution and in developing methodologies to translate PE fit information into valid and workable study advice. The method proposed in the current work introduces a novel way of translating PE fit into student orientation. Compared to more traditional and mainly convention-based congruence index approaches to PE fit and study orientation, this new methodology ensures the creation of advice sets, balanced in length (to enable environment exploration) and fit quality (in terms of correlation PE fit). In sum, EASE may be a promising way to rethink how student PE fit information can be used in both fundamental research and practical applications regarding student orientation and higher education research.

Note

1. None of the 62 study programs had a RIASEC code starting with C, although students exist for which this is the dominant RIASEC dimension.

Acknowledgments

The current manuscript is a direct result of a larger longitudinal project called SIMON (Study Success and Interest Monitor), which focuses on dispensing study advice to prospective students.

Funding

The SIMON project is funded using Ghent University resources. The funding source had no direct involvement in study design, in the collection, analysis, and interpretation of data, in the writing of the report, or in the decision to submit the article for publication. EASE research findings were partly presented at an EARA conference in the form of a poster presentation (September 14, 2018, Ghent University).

ORCID

Stijn Schelfhout http://orcid.org/0000-0001-9531-304X

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Appendix A

SIMON-I questionnaire

Appendix A

Part 1: Activities

Mark the YES column for activities you enjoy or activities you would like to try. Mark the NO column for activities you would not like to do. If you really don't know what the activity involves, skip the item.
Dimensions were masked for the participant.

	Dimension	YES	NO
Developing electronic systems	R		
Analyzing the grammatical structure of a sentence	I		
Helping people with speech disorders	S		
Recruiting a job candidate	E		
Monitoring the quality standards for food safety and hygiene	C		
Repairing malfunctioning electrical equipment	R		
Carrying out laboratorial analyses	I		
Designing a poster for an exhibition	A		
Helping others with their personal problems	S		
Organizing a conference	E		
Preparing financial reports	C		
Being responsible for the maintenance of IT hardware	R		
Analyzing statistics	I		
Designing webpages	A		
Developing council prevention campaigns	S		
Presenting new policy propositions	E		
Collecting quantitative and qualitative data	I		
Developing new methods for industrial production	R		
Treating diseases in animals	I		
Editing the sound and images for a movie	A		
Formulating education and training policies	S		
Drawing up budgets	C		
Doing the follow-up on building sites	R		
Analyzing x-rays/brain scans	I		
Setting up a show room	A		
Offering sports guidance for children, the elderly, …	S		
Formulating theory about the differences between population groups	I		
Monitoring quality standards	C		
Maintaining airplanes	R		
Investigating the impact of historical people	A		
Composing a work of music	A		
Providing guidance for victims	S		
Selling a product or service	E		
Calculating prices	C		
Installing and maintaining computer servers	R		
Designing an advertising folder	A		
Providing information about assistance for the poor	S		
Creating an organizational business or policy plan	E		
Checking bank transactions	C		
Developing windmill parks	R		
Proving a theorem	I		
Analyzing text structures	A		
Giving travel advice	S		
Negotiating contracts	E		
Drawing up a contract	C		
Investigating chromosomal defects	I		
Writing scenarios	A		
Conducting tests, administering questionnaires, and conducting in-depth interviews	S		
Screening the administration	C		
Working on a drilling rig	R		
Turning an idea into a film	A		
Giving care to patients	S		
Restructuring an organization or company	E		
Checking regulatory compliance	C		

(*continued*)

Appendix A Continued.

Part 1: Activities	
Excluding alternative explanations through experiments	I
Designing the layout of a hospital	A
Advising youngsters regarding their vocational choice	S
Exploring new economic markets	E
Drawing up a company's annual report	C
Setting up a festival stage	R
Developing a new medicine	I
Writing a review	A
Giving training in communication skills	S
Starting up an enterprise	E
Investigating a cost structure	C
Creating a technical drawing	R
Putting theories in their historical and social context	I
Creating an art piece	A
Giving health advice	S
Giving health and parenting education	E
Calculating expenses	C
Disassembling electrical appliances	R
Comparing cultures	A
Assisting minority groups with job searches	S
Conducting a meeting	E
Drawing up a timetable	C
Measuring a lane	R
Supporting and following up with foster families	S
Attracting sponsors	E
Teaching a class of students	S
Leading a team	E
Managing a database	C
Collecting soil samples	R
Beginning a herbarium (a plant collection)	I
Counseling underprivileged people	S
Formulating a treatment plan	S
Studying the physical endurance of athletes	I

Part 2: Occupations

Mark YES for professions you would like to practice or that you would like to try. Mark NO for professions you would not like to practice. If you think a little bit, you probably know most professions. If you really don't know what a profession entails, skip the item.
Dimensions were masked for the participant.

	Dimension	YES	NO
Industrial designer	R		
Civil engineer	I		
Fashion designer	A		
Policy advisor in political and international relations	E		
Recruitment and selection advisor	E		
Damage expert	C		
Agricultural technician	R		
Teacher	S		
Business economist	C		
Accountant	C		
Electrical engineer	R		
Biologist	I		
Art/music teacher	A		
Speech therapist	S		
Bank manager	C		
Landscape architect	R		
Physicist	I		
Editor	A		
Student counselor	S		
Tax supervisor	C		
Neurologist	I		
Policy advisor art and culture	A		

(*continued*)

Appendix A Continued.

Part 2: Occupations	
Educator	S
Marketing manager	E
Safety advisor	C
Construction manager	R
Historian	I
Director	A
Communication manager	E
Manager (of a company)	E
Judge	C
Forester	R
Researcher	I
Graphic designer	A
Psychologist	S
Lawyer	E
Notary	C
Mathematician	I
Art historian	A
Social worker	S
Politician	E
Pilot	R
Pharmacist	I
Linguist	A
Divorce mediator	S
Journalist	A
Structural engineer	R
Lab assistant	I
Photographer	A
Nurse	S
Advertising campaign manager	E
Chemist	I
Tax specialist	C
Architect	R
Artist	A
Educational scientist	S
Librarian	A
Philosopher	I
Representative	E
Geneticist	I
Interior designer	A
Estate agent	E
Physiotherapist	S
Meteorologist	I
Sales manager	E
Statistician	I

Appendix B

EASE Manual and Executable RStudio Code: An Example for One Student

1. Obtain the RIASEC profile of the student. For instance, R = 17, I = 59, A = 12, S = 14, E = 0, C = 9. For this example, scores are scaled from 1 to 100. Any vocational interest instrument (or scaling) can be used as long as it covers all six RIASEC dimensions.
2. Obtain the RIASEC profiles of the programs. For instance, a bachelor's in mathematics has a profile of R = 25.98, I = 41.01, A = 28.52, S = 24.81, E = 26.04, C = 33.03. Scores are scaled from 1 to 100. Again, any instrument (or scaling/method) can be used as long as it covers all six RIASEC dimensions. For this example, we used an incumbent method as described by Allen and Robbins (2010) to construct 62 program profiles.
3. Obtain the correlation between the student and each of the program profiles. For instance, correlating the profiles from the student and mathematics program yields $r = .83$. For this example, we correlated the student profile with each of the 62 program profiles. For obtaining this multitude of correlations, we advise using an Excel worksheet. Insert student profile and mathematics profile in one horizontal row; you can add

a horizontal identifier and column headings if so desired. For instance, cells A1 to F1 contain the student RIASEC profile, and cells H1 to M1 contain the mathematics RIASEC profile. Enter the code for the correlation in cell G1, "*=CORREL($A1:$F1;H1:M1)*."

4. Add the next program profile using the same procedure. As such, leave one space, N1, for the correlation code and insert the RIASEC dimension scores of the program in cells O1 to T1. Copy and paste the correlation code from G1 to N1. The fixed student profile cells, indicated by a dollar sign, will remain in place, while the profile cells will change from H1:M1 to O1:T1. Repeat the procedure for all programs. For future reference, adding new student profiles can be done by using a new row for each student. Add student profiles using columns A to F. Copy the remainder of the program data (and the correlations) by selecting the top row and double right clicking on the lower right corner of your selection. To make a file containing only the correlation values, copy the values (not the formulas) of the entire file (sheet) to a new file and delete everything but the correlations (or optional identifiers).
5. For the present example, we have listed all programs and their correlations to the student profile at the end of this appendix. Create the Excel file "onestudent" by pasting the 62 correlations (with optional programs as column titles) in cells A1 to BJ1 of an Excel sheet. Name the Excel file "onestudent." The correlations do not need to be ranked.
6. Import the Excel data file "onestudent" into R (Studio). As you import the code, do indicate if your file contains column titles. Paste the EASE executable code (see below) into an R(studio) script; load the packages mentioned and follow instructions where needed. Run the EASE R-script with "onestudent" as input. We have annotated the code with editorial comments to clarify the application and to link this application to the EASE paper. Comments are annotated in bold and preceded by #.

```
### EASE executable code
## load packages broom, lsr, psych, import excel sheet onestudent
# for other datasets, simply replace onestudent with the name of your datafile and load the file
# declaring matrices for matters of easier programing

mydata = onestudent
mydata = as.matrix(mydata)
Dprep = mydata
Dprep = as.matrix(Dprep)
Dprep = t(Dprep)
testmatrix = mydata
testmatrix = as.matrix(testmatrix)

# declaring integers; integers are always determined by the dimensions of the dataset
# for the current dataset x = 1 (students) and y = 62 (programs)

x = nrow(mydata)
y = ncol(mydata)

# declaring results matrix and aid matrix D
# result file has room for up to 40 variables, only 6 are used for the current application

results = matrix(nrow = x,ncol = 40)
D = matrix (nrow = y, ncol = 1)

# EASE algorithm for each student separately (cross-validation),
# indicated by the i in the for-loop
# this example only has one student (x = 1), the algorithm can run thousands of students
# mainly depending on the processing power available
# (cfr main paper, 7,063 and 4,892 students)
# each different value for i will represent a different student
# with a different model estimation, threshold, and advice set (size)

for (i in 1:x) {

# ordering correlations for one student from low to high

Dprep = Dprep[order(-Dprep[,i]),]
```

```
Dprep = as.matrix

# using an aid matrix D to calculate the parameters
# correlation (fit quality), correlation^2, options and balance

D[,1] = Dprep[,i]
D = as.data.frame(D)
D$correlation = D$V1
D$correlation2 = D$correlation * D$correlation
D$options = seq(from = 1, to = y)
D$balance = D$correlation * D$options

# fitting quadratic (parabola) model ax^2 + bx + c

fit = lm(balance ~ correlation2 + correlation, data = D)
summary(fit)

# plotting fit

par (cex = .8)
timevalues = seq(-1, 1, 0.01)
predictedcounts = predict(fit,list(correlation = timevalues, correlation2 = timevalues^2))
plot(D$balance ~ D$correlation, col = "blue")
lines (timevalues, predictedcounts, col = "darkgreen",lwd = 3)

# extracting fit measure (R^2) for the parabola model

results[i,1] = summary(fit)$r.squared

# extracting parameter weights a, b and c

coeff = tidy(summary(fit)$coefficients)
a = coeff[2,2]
b = coeff[3,2]
c = coeff[1,2]

# determining (ideal fit) threshold of the model ax^2 + bx + c

ithreshold = (-1*b)/(2*a)

# extracting (ideal fit) threshold of the model ax^2 + bx + c

results[i,2] = ithreshold

# extracting confidence interval ideal threshold

confint1 = confint_tidy(fit,conf.level = 0.95)

# calculating the boundaries of the confidence interval (confintlow, confinthigh)
# using the confidence intervals of the parameter weights

confint2alow = -2*confint1[2,1]
confintblow = confint1[3,1]
confintlow = confint1[3,1]/(-2*confint1[2,1])
confinthigh = confint1[3,2]/(-2*confint1[2,2])

# extracting the boundaries of the confidence interval using the confidence intervals of the
# parameter weights
# confintlow corresponds to the actual threshold
```

```
results[i,3] = confintlow
results[i,6] = confinthigh

# testing uniformity of PE fit distribution

fit2 = lm(options ~ correlation, data = D)
summary(fit2)

# extracting estimation of uniformity of PE fit distribution

results[i,4] = summary(fit2)$r.squared

# how many choices does the student receive as part of his/her advice set?

results[i,5] = length (which (testmatrix[i,] > confintlow))
}

# extract all results, adapt the path "C:/school/Revision paper 1 jee/" to where you want the
# "results" text file
# results include (from left to right)
# the fit of the EASE model (.996),
# the ideal threshold (.52),
# the actual threshold (.50),
# an estimate of the uniform distribution of PE fit in this specific student (.984
# size of the advice set (18)
# the upper boundary of the confidence interval of the ideal threshold (.55)
# 34 empty slots, placeholders for possible additional variables

write.table(results, "C:/school/Revision paper 1 jee/results", sep="\t")

### end
```

7. Besides the results from the algorithm, the actual threshold (.50) can be cross-referenced to the list of programs and their PE fit (correlations) with the student profile to determine which programs exactly will be part of the advice set. In this case, all programs (18) with a PE fit over .50 are part of the advice set up to and including *industrial science: chemistry* (see below). The example also indicates that the student has an interest profile corresponding to hard science programs, though not all hard science programs are part of the advice set. This process can be automatized further through use of an Excel sheet or straight in the R-code if so desired.

programs	PE fit
biochemistry and biotechnology	.98
bioscience engineering: cell and gene biotechnology	.93
biology	.93
biomedical science	.89
physics and astronomy	.88
geology	.85
bioscience engineering: land and forest management	.84
mathematics	.83
veterinary medicine	.81
psychology: theoretical and experimental psychology	.81
chemistry	.80
pharmaceutical science	.80
bioscience engineering technology	.78
environmental engineering technology	.72
engineering: applied physics	.72
computer science	.67
bioscience engineering: environmental technology	.61
industrial science: chemistry	.55
geography	.49
dentistry	.47

(*continued*)

Continued.

programs	PE fit
archaeology	.45
bioscience engineering: agricultural science	.45
bioscience engineering	.44
medicine	.42
chemical engineering and materials science	.41
rehabilitation science and physiotherapy	.39
electrical engineering	.27
electromechanical engineering	.15
philosophy	.13
sociology	.13
physical education and movement science	.12
moral science	.10
African languages and cultures	.08
speech language and hearing science	.07
computer science engineering	.04
psychology: clinical psychology	.04
geomatics	.04
industrial science: electronics-ICT	.02
engineering: architecture	.01
industrial science: electro-mechanics	.01
information engineering technology	−.01
civil engineering	−.03
oriental languages and cultures	−.04
language and literature (two languages of choice like English and Dutch)	−.08
educational science: special education, disability studies and behavioral disorders	−.10
criminological science	−.11
East-European languages and cultures	−.13
art history, musicology and theater studies	−.14
history	−.16
educational science: pedagogy	−.17
industrial design engineering technology	−.24
applied linguistics	−.24
civil engineering technology	−.30
economics	−.32
communication science	−.42
psychology: personnel management and industrial psychology	−.44
business engineering	−.45
political science	−.47
law	−.54
public administration and management	−.56
business economics-	−.58
business administration	−.61