How Interest Fit relates to STEM Study Choice:

Female Students Fit their Choices Better.

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Abstract

STEM (Science, Technology, Engineering and Mathematics) enrolments in higher education are declining while the STEM gender gap of female underrepresentation seems to widen. The present study addresses both issues by exploring how the fit between a student's vocational interests and the STEM field contributes to a (non-) STEM study choice. Data was collected in the unique setting of an open access and low cost higher education system, which allowed for study of vocational interests without unwanted influence of admission conditions. Specifically, we assessed the interest fit of *N* = 9,162 first-year Belgian university students with (1) the STEM field (i.e., STEM fit) and (2) their specific program of choice (i.e., program fit). Results indicated STEM fit indeed predicted STEM study choice, with a stronger effect in female students. Results also indicated that female students showed a better specific program fit. In order to promote student STEM enrolment and address the gender gap, the present study therefore advocates a gender-specific approach to attract more students with appropriate interest profiles.

Keywords: *PE interest fit; person-environment interest fit; STEM; STEM fit; STEM gender gap; STEM profile; STEM study choice*

Introduction

STEM (Science, Technology, Engineering and Mathematics) study choice has become an important topic in vocational and educational literature as study choice is the primary gateway to the STEM work field (UNESCO, 2016). Reports have shown that keeping this STEM work field well-staffed can be crucial to the economy of industrialized countries (World Economic Forum, 2016). However, this primary STEM gateway of higher education enrolment faces two major challenges. First, literature reports a decline in the number of students choosing a STEM program in higher education (Ainley et al., 2008; Perera & McIlveen, 2018). Second, literature also reports a widening gender gap in enrolments, indicating a still growing female underrepresentation (Stoet & Geary, 2018; Xu, 2008). For instance, according to numbers from the United Nations Educational Scientific and Cultural Organization (UNESCO), female students only represent 35% of all students enrolled in higher education STEM programs and female researchers only account for 28% of all researchers active in the field (UNESCO, 2016).

One approach to addressing these issues consists in determining how a student that chooses a STEM program differs from a student that chooses a non-STEM program. Comparing both options can render more information on which (future) students would have a suited profile for a career in the STEM field. Such information can then be used in future studies or interventions on how to guide these students towards the STEM field. In order to facilitate such a distinction, vocational interests are a valid option, as interests are arguably considered the strongest predictors of study choice (Stoll et al., 2017). For instance, a good fit between a student's vocational interests and a student's study environment has predictive validity towards study choice, persistence and results (Burns, 2014; Donnay, 1997; Nye et al., 2012; Rounds & Su, 2014; Schelfhout et al., 2021; Schelfhout et al., 2019). However, literature does not yet report on the effect of this person-environment interest fit (PE interest fit) towards STEM study choice. Moreover, gender differences regarding this PE interest fit also have yet to be investigated. Such gender differences could prove important as literature shows that known predictors of STEM study choice do interact with gender (Yazilitas et al., 2013). For instance, a STEM study choice in female students is less determined by performing well in specific STEM preparation courses like mathematics, as women evaluate their cognitive capabilities much more modestly compared to men (Nix et al., 2015).

The present study has two research goals. First, we want to investigate how PE interest fit contributes to the prediction of STEM study choice by comparing a STEM choice versus a non-STEM choice. Particular consideration is hereby given to interaction effects with gender. Second, we want to investigate whether and to which extent male and female students differ regarding PE interest fit with their specific STEM program. With the answers to our questions, STEM study orientation can act upon this knowledge to increase (female) student STEM enrolments by focusing their efforts on recruiting students with appropriate profiles through means of policy and counseling.

The RIASEC Model of Vocational Interests

Today, the RIASEC model by Holland (1997) is still one of the most influential models in vocational literature, describing the interest profiles of students and their study programs through six RIASEC dimensions (realistic, investigative, artistic, social, enterprising and conventional). This model also displays an empirically verified circular structure: the dimensions are arranged in clockwise RIASEC order (Tracey & Rounds, 1995). To obtain an individual student’s RIASEC profile, the literature describes a vast number of questionnaires, all rendering scores on the six dimensions (for an overview, see Nauta, 2010). For the present study, we used

SIMON-I, a validated instrument specifically targeting the transition from high school to higher education (Fonteyne, Wille et al., 2017). To obtain an environment program profile, student profiles can function as representatives or *incumbents* for their program of choice. As an example for the present study, we thus established a RIASEC profile for each specific study program by averaging RIASEC scores of successful and persistent students enrolled in that specific program (Allen & Robbins, 2010). As the present study also focuses on STEM as a separate educational environment, we additionally established a RIASEC interest profile for the entire STEM field by averaging the RIASEC scores of all study programs classified as STEM. This operationalization of the STEM field is empirically verified in the present study's *Method and Materials* section.

Person-Environment Interest Fit

As the RIASEC model allows for commensurate measurement (i.e., measurement on the same scales) of both individual and program profiles (Holland, 1997), we can also determine how well an individual (i.e., a student) fits an environment (i.e., a study program or the STEM field). This concept of PE interest fit is well-established in literature (Nye et al., 2012), and operationalized using different measures with different properties. For an overview and discussion, we refer to Nye and colleagues (2018). As an example, Euclidean distance operationalizes PE interest fit in terms of the distance between the person and the environment profile in two-dimensional space. Specifically, this approach relies on the Prediger dimensions of *People / Things* (P/T) and *Data / Ideas* (D/I) to define the person and environment profiles (Prediger, 1982; Prediger, 2000). In practice, coordinates are determined using the following formulae,

$$P\,/\,T\ = 2R + I - A - 2S - E + C \tag{1}$$

$$D\,/\,I = 1.73E + 1.73C - 1.73I - 1.73A \tag{2}$$

and Euclidean distance (ED) is calculated as

$$ED = \sqrt{(student\ P/T\ \ - \text{study program}\ P/T\ )^2 + (student\ D/I\ \ - \text{study program}\ D/I)^2} \tag{3}$$

with P/T, D/I and ED as a function of the scores on the RIASEC dimensions (Wille et al., 2014).

Although other PE interest fit metrics are also available, we have selected Euclidean distance as measure of PE interest fit for the present study as the measure's properties facilitate our research goals. First, evidence has shown that a low Euclidean distance indeed predicts study degree attainment (end of the third year of higher education) from as early as the first year of higher education (Tracey et al., 2012). Degree attainment also forms the primary gateway towards the STEM work field (UNESCO, 2016). As our data were gathered in a student population making the transition from secondary education to the first year of higher education, Euclidean distance is an appropriate measure to investigate the effect of PE interest fit on a (non-) STEM choice.

And second, Euclidean distance also allows to locate not only students, but also study programs in two-dimensional Euclidean space. For the present study, locating programs allows us to empirically verify the difference between STEM programs and non – STEM programs as a function of their position in Euclidean interest space. This empirically verified distinction between a STEM choice and a non – STEM choice adds to literature as previous studies primarily focused on differences *within* the STEM field to characterize STEM profiles. Indeed, what was considered a typical STEM profile was determined by comparing that profile to the STEM field exclusively (Su & Rounds, 2015; Su et al., 2009). For instance, Perera and McIlveen (2018) reported that students with specific latent interest profiles (i.e., high realistic dominant and conventional dominant) have a higher chance of making a STEM choice in higher education. Perera and McIlveen (2018) operationalized their study by describing typical latent profiles that are present in the STEM field, without reporting how vocational interests directly contribute to making a STEM choice over a non-STEM one. In contrast, the present study actively profiles how a STEM student differs from a non – STEM student in terms of individual RIASEC scores and PE interest fit by regressing STEM study choice on vocational interest variables. For these purposes, we consider two applications of PE interest fit to address the contribution of interest fit to a STEM study choice over a non - STEM study choice: STEM fit and program fit. *STEM fit* measures the Euclidean distance between a student's RIASEC profile and the broader STEM field profile. This index thus allows to investigate how the interest profile of a student choosing a STEM program differs from the profile of a student choosing a non-STEM program. In contrast, *program fit* measures the Euclidean distance between a student's RIASEC profile and the RIASEC profile of the specific study program that was chosen, which can be either within or outside of the broader STEM field. This program fit is used to compare PE interest fit between male and female students in specific programs.

Vocational Interests and STEM Study Choice

Meta-analytic research by Low and colleagues (2005) has shown that vocational interests are quite stable from early adolescence (i.e., about age 12) to middle adulthood (i.e., about age 40). This early stability in the lifespan makes vocational interests a good candidate for (study) career orientation as one's interests as a student have a good chance to persist into adulthood. Indeed, literature shows vocational interests can predict up to 70% of the variance in study choice across students (Burns, 2014; Donnay, 1997; Päßler & Hell, 2012; Nye et al., 2012;

Rounds & Su, 2014; Stoll et al., 2017). For instance, high realistic and investigative interests in incoming students are predictive of becoming a civil engineer (Fonteyne, Wille et al., 2017). Apart from individual student vocational interests, study environment characteristics regarding vocational interests are arguably equally important in the process of study choice. Specifically, these characteristics codetermine the level of PE interest fit between student and study program, contributing to study choice above and beyond the effects of individual student vocational interests. To give one example, Schelfhout and colleagues (2019) found an average similarity of about 49% (r = .70) between the RIASEC profile of an individual student and the RIASEC profile of the chosen study program (based on the RIASEC profiles of students who successfully completed that program). In other words, a higher level of PE interest fit between the RIASEC profiles of students and their study programs enlarges the chance that the student will choose the program eventually.

Analogous to the previous example, the present study uses the RIASEC profiles of successful STEM students to determine the RIASEC profile of STEM study programs and the broader STEM field as a whole. We thus expect that students making a STEM study choice will have similar RIASEC profiles that have a better fit with the STEM field compared to the RIASEC profiles of students who do not make a STEM study choice. This similarity assumption also seems plausible as students making a STEM study choice should have a profound and stable interest in science, technology, engineering and mathematics, similar to graduated students that have finished their STEM education and are ready to enter the STEM work field. We thus hypothesize that a student's PE interest fit with the STEM field should have predictive value towards a STEM study choice,

Hypothesis 1: *STEM fit predicts STEM study choice.*

Moreover, literature already shows that predictors of STEM study choice often interact with gender (Germeijs & Verschueren, 2006; Nix et al., 2015; Yazilitas et al., 2013). As such, the present study also gives particular consideration to the interaction effect between gender and

PE interest fit on STEM study choice, as such an effect can shed new light on existing issues like the female underrepresentation in the STEM field (Xu, 2008) and a decline in enrolments (Ainley et al., 2008). To investigate this interaction effect, we consider the leveled framework by Yazilitas and colleagues (2013). This framework reviews the relevant literature regarding STEM[1] study choice using an institutional level focus, a macro-level focus and a micro-level focus. The institutional level explains gender choice patterns as a result of education policies. The macro-level explains these patterns as a result of societal patterns. And the micro-level explains these patterns as the result of psychological constructs. Yazilitas and colleagues (2013) stress that these three foci are not operating within a vacuum but instead interact with each other.

Gendered Choice Patterns at the Institutional Level

The effect of PE interest fit on STEM study choice may vary depending on educational policy of institutions or regions. For example, the present study is conducted in an open access and low cost higher education system, where anyone with a high school degree can enroll for almost any study program. Such a context provides a unique opportunity to assess the effect of PE interest fit on study choice without risk of unwanted bias from high stakes testing or GPA (grade point average) requirements. As a consequence, not only do students have to make a choice regarding a bachelor program (i.e., 39 programs in the present study), but students also need to make a choice of university or college (Fonteyne, 2017; Schelfhout, 2019). Such a stressful event can even induce a *paradox of choice*, as too much choice can have negative consequences (Schwartz, 2015). For example, Abbiss (2009) reported that more options actually reinforce gender stereotypes in an information and communication technology program. As such, a broad choice does not seem likely to drive female STEM study choice. However, such a stressful event also creates opportunities for female students. In a neurocognitive study, Preston

[1] This early review did not consider Engineering as a separate academic field.

and colleagues (2007) examined decision-making of males and females in stressful situations. Results showed that females make better decisions, while also making better use of explicit knowledge. As such, a stressful study choice could lead to a better interest fit in female students as females make better decisions in stressful situations. However, we have to consider the macro- and micro-level of the framework to investigate which explicit knowledge female students use and how this knowledge can lead to better decisions (Yazilitas et al., 2013).

Gendered Choice Patterns at the Macro-Level

Gendered choice patterns have also been attributed to social or cultural determinants. For instance, a large international study by Stoet and Geary (2018) shows that in developed, progressive and gender-aware countries the need to choose STEM education for instrumental reasons like job prospects and salary is smaller. As a consequence, women are more likely to choose non-STEM programs, effectively increasing the gender gap in these more gender-aware countries. This gender gap originates as early as primary school, and is strongly tied to STEM preparation (Bagiati et al., 2010; Bybee, & Fuchs, 2006). Such early STEM preparation takes the form of exposure to science and mathematics and has a large positive impact on the pupil's disposition towards STEM (Blackburn, 2017; Dejarnette, 2012). The gender gap from primary school is then further consolidated into secondary education. For instance, girls remain underrepresented in STEM preparing high school programs that focus on mathematics (Sadler et al., 2012; UNESCO, 2016). Wang (2013a; 2013b) also reports that such an exposure to mathematics in secondary education leads to an intent to major in academic STEM programs and thus predicts a choice for STEM in higher education. Because better high school performance is associated with more STEM study choice (Vaarmets, 2018), and because women outperform men in high school (Buchmann et al., 2008), one would expect that the minority of women that are still represented in STEM preparing programs should have a higher chance of choosing STEM. However, Nix and colleagues (2015) report the opposite: female students in STEM preparing programs have a lower chance of choosing STEM. According to Nix and colleagues (2015), this discrepancy originates from the fact that women estimate their cognitive capabilities much more modestly. As such, explicit knowledge of STEM preparation has less impact on female STEM choice. STEM preparation is therefore not an answer to our question which explicit knowledge would lead to a better decision and a better PE interest fit in female students. Considering the importance of the effect of STEM preparation on STEM study choice, we have included STEM preparation in our analyses of the present study as a control variable.

Gendered Choice Patterns at the Micro-Level

Besides these macro – level environmental influences, making a study choice is an important life decision that also involves micro – level individual cognitive decision processes (e.g., What do I want to do in my future professional life?) (Fonteyne, 2017; Schelfhout, 2019). Social cognitive theory (SCT) is a theory on human behavior that considers both the influence of the social environment as well as the influence of individual cognition (Bandura, 2001; Lent, 1994). According to SCT, human behavior can be explained through three psychological determinants: self-efficacy beliefs (i.e., can I do it?), outcome expectations (i.e., what will happen?) and goal representations (i.e., what will I gain?). Self-efficacy is regarded as the most important one, as it determines if an individual has sufficient self-belief to start a specific task to begin with (Stajkovic & Luthans, 1998a; Stajkovic & Luthans, 1998b). In social cognitive career theory (SCCT), self-efficacy is also considered an important precursor of the effect of vocational interests on STEM-study choice (Lent & Brown, 2019). For instance, in a series of studies on choice goals towards computing majors (a STEM choice), the total SCCT model explains about

40% of the variance in vocational interests, with self-efficacy forming the most important determinant (Lent et al., 2008; Lent et al., 2011). In their own right, vocational interests also had a significant influence on the goal of choosing a major in computing, alongside the direct effect of self-efficacy, social support and social barriers.

For the present study, student self-belief that a study choice is a good fit with personal vocational interests is a necessary condition to make an appropriate STEM study choice. Such a self-belief does assume that a student has sufficient explicit knowledge about his or her own interests and STEM study choice to begin with. To facilitate such knowledge, Germeijs and Verschueren (2006) validated a study choice task inventory (SCTI) based on existing instruments and newly introduced items. In an open access environment, the SCTI measured the orientation, exploration and commitment of 946 high school students towards study choice. Results indicated that girls scored higher on orientation (e.g., "I often think about what I will study"), exploratory behavior of environment (e.g., "I thoroughly read a brochure about these studies"), self-exploratory behavior (e.g., "I have talked with my friends about my interests") and commitment (e.g., "Are you uncertain about this study?"). In sum, future female students seem to have more explicit knowledge about their interests and possible study choices, while also making more and better use of that explicit knowledge (Germeijs & Verschueren, 2006). As such, we consider that female students could ponder more explicitly over the question whether a STEM choice fits their personal interests. If a female student believes she has a good interest fit with the STEM field, chances are she will make more use of this explicit information compared to her male colleagues. As such, we hypothesize that

Hypothesis 2: *The effect of STEM fit on STEM study choice is moderated by gender, with a stronger effect in female students.*

For the present study, study choice is more than just a choice for STEM or non-STEM. Students primarily have to make a choice for a specific topic, that is implemented in a specific study program (i.e., somewhat comparable to a major). As such, future STEM students can choose programs like chemistry and computer sciences, while future non-STEM students can choose programs like philosophy or law. Analogous to hypothesis 2, we again consider that female students could ponder more explicitly over the question whether the specific program choice fits their personal interests. If a female student believes she has a good interest fit with the specific STEM program, chances are she will make more use of this explicit information compared to her male colleagues. As such, we hypothesize that

Hypothesis 3: *Female STEM students have a better program fit with their program of choice compared to male students.*

Moreover, if a better program fit for female students is indeed the result of more explicit knowledge regarding their own interests and their program choice, this gender effect should also be found in non-STEM study programs in addition to STEM programs. To test this assumption, we will also investigate hypothesis 3 in the general student population, across all 39 (STEM and non-STEM) programs. The results of this test will allow us to answer our second research question whether and to which extent male and female students differ regarding PE interest fit with their specific STEM program.

Method and Materials

STEM Field, Stream and Approach

STEM does not have an unequivocal definition in literature. For the present study, we have thus operationalized STEM as defined by UNESCO. UNESCO defines the STEM concept through the perspectives of field, stream and approach (UNESCO, 2016). As a *field*, STEM incorporates life sciences, physical sciences, technology, engineering and mathematics. As a *stream*, the STEM field enrolls students from secondary education into a program in higher education. Finally, as an *approach*, the STEM field aims at an application of the studied knowledge, skills and values to help solve problems in the real world.

The present study focuses on the first two elements of the UNESCO definition. First, we applied the field definition of STEM to the present data, effectively distinguishing a STEM study choice from a non-STEM one. Second, the STEM stream takes the form of student data gathered within the context of study orientation. The transition from high school to a higher education is indeed considered as a crucial timing to recruit future employees as students enroll for STEM oriented programs in higher education.

Data and Procedure

We applied the UNESCO definition to student data collected within all faculties and all programs (STEM and non-STEM) of a Belgian university (Shanghai Top 100, which ranks the world's top 1,500 universities and colleges based on objective measures). The data are part of the university's longitudinal project for study orientation (Fonteyne, 2017; Schelfhout, 2019). This orientation project focuses on the transition of individuals from high school to higher education by guiding these future students towards appropriate study programs, based on their skills (i.e., which programs are obtainable?) and also their vocational interests (i.e., which programs are interesting to me?). Orientation for these students is needed, as they are enrolling in unconstrained, open access and low cost higher education, with nearly limitless options in programs to choose from. Indeed, barring the exceptions of Medicine, Dentistry or Performing Arts (music), all academic higher education programs are open to everyone with a high school degree. Moreover, the tuition fees do not exceed € 1,000 or about $ 1,150, and almost half of the students receive funding through scholarships, based on economic (income-related) criteria. Also, the orientation instrument does not show bias towards social economic status or towards people with a different nationality (4% of the student population) or towards Belgians with a foreign origin (1% of the student population had at least two grandparents that were not Belgian) (Fonteyne, 2017). About 20% of all students did not want to disclose whether they had a foreign origin.

For the present dataset, it is important to point out that students starting the same study program have identical curricula, resulting in a highly comparable study choice. Moreover, once students have made their choice for a specific program, they cannot interchange elements of their curriculum in later years of the program. As an example, students do not have the possibility of "changing major" after a successful first or second year, as is more custom in British or American systems. A first year STEM study choice thus becomes highly predictive towards future employment in the STEM field. Taken together, the present study's educational setting allows for study of vocational interests without unwanted effects from high stakes testing, GPA requirements or financial attainability.

At the start of the academic years 2016-2017 and 2017-2018, two cohorts of newly enrolled students participated in this online study (September-October 2016 and 2017). Participation was not mandatory, but promoted through professors, email and the online learning platform used in all university programs. The student data from the programs Medicine and Dentistry were excluded from the present study as students had to pass an exam to enroll for the program and thus formed the only exception regarding open access study context. The overall response rate was 68% (N = 9,162, 60% female), with 3,389 students choosing a program in the STEM field.

We also assessed the interest profiles of 39 study programs (see also Figure 1), using the interest RIASEC profiles of former successful and persistent senior students, who indicated they would enroll again for the same program when given the opportunity (N_0 = 6,572). These senior students met the conditions of perseverance and academic success and the procedure of establishing the program profiles was identical to the procedure used by Allen and Robbins (2010). For each program, the RIASEC scores of all students were averaged for each dimension, resulting in a RIASEC profile for each program.

Measures

STEM or non-STEM Study Choice

UNESCO operationalizes the STEM field as a field that incorporates life sciences, physical sciences, technology, engineering and mathematics (UNESCO, 2016). Importantly, this UNESCO operationalization does not include social sciences, in contrast to some studies (Su & Rounds, 2015). As such, all 39 programs are divided into STEM and non-STEM programs based on the UNESCO definition (UNESCO, 2016) so that students in a (non-) STEM program are considered to have made a (non-) STEM study choice. Figure 1 shows a scatterplot of all program profiles, by representing each profile as a single point in Euclidean two-dimensional space. We proceed by defining the general STEM field profile by averaging interest dimension scores across all STEM programs to correct for student numbers in the programs. This calculation results in a STEM field RIASEC profile with the following dimension scores, R = 31.88, I = 46.25, A = 28.99, S = 24.54, E = 26.32 and C = 21.15. Figure 1 shows that programs categorized as STEM according to the UNESCO definition are centered alongside a regression line, in the things/data quadrant. Figure 1 also shows that the social sciences are distanced from this cluster, warranting their exclusion from the STEM field. Figure 1 thus provides empirical support for our UNESCO operationalization of the STEM field.

Vocational Interest

We used the SIMON-I questionnaire to obtain vocational interest scores on the six RIASEC dimensions (see Appendix A; Fonteyne, Wille et al., 2017). The RIASEC dimension scales showed a reliability (Cronbach's α) of .92, .88, .92, .92, .93 and .90 respectively. To test the assumed circular structure of the RIASEC dimensions, we first performed a confirmatory factor analysis (CFA), using the CirCe package in R (Browne, 1992; Grassi et al., 2010). The analysis confirmed the circular structure (SRMR = 0.05, NFI = 0.97, CFI = 0.97, GFI = 0.99) and the parsimony (Schwarz's Bayesian Criterion of 0.03) of the RIASEC dimensions. Second, we also performed a *randomization test of hypothesized order relations* (RTOR) using the RANDALL package to confirm the circular structure and order of the RIASEC dimensions (Tracey, 1997). Results of this RTOR analysis revealed a *correspondence index* of CI = .92, p = .02, indicating an excellent fit. Both CFA and RTOR analysis thus support the circular structure of the RIASEC data.

STEM Fit and Program Fit

STEM fit indicates the PE interest fit between a student (i.e., individual RIASEC profile) and the general STEM field (i.e., STEM field RIASEC profile) and is measured in Euclidean distance. Program fit indicates the PE interest fit between a student and her/his specific program (i.e., RIASEC program profile) and is also measured in Euclidean distance. We calculated Euclidean distance as described in the introduction (Wille et al., 2014).

STEM Preparation

Wang (2013a; 2013b) already reported that exposure to mathematics predicts the choice of a STEM program in higher education and thus prepares students for the STEM field. As such, for the present study, we have operationalized STEM preparation as weekly hours of high school mathematics prior to higher education enrolment. This variable has already been used for various other purposes in literature. For instance, several open access studies have found that weekly hours of mathematics in high school also predicts higher education study success (Fonteyne, Duyck, et al., 2017; Pinxten et al., 2017).

Analyses

To test hypotheses 1 and 2 (H1 and H2 respectively), we constructed a STEM study choice model, which is a logistic regression of STEM study choice on the main effects and gender interactions of STEM preparation, PE interest fit and all six individual RIASEC interest dimensions. Though the logistic model is tailored towards STEM study choice, the model also represents a non-STEM study choice as the outcome is binary (i.e., 1 or 0). As STEM is the focus of this study, we formulated the results in terms of STEM study choice. The model was built in two stages by first adding all main effects, followed by all gender interactions. Individual RIASEC dimension effects and their interactive effects with gender were included as control variables in this analysis in order to obtain a conservative and more precise estimate of the PE interest fit effect. As our distinctive model has to deal with a fairly large number of predictors, we used Akaike's Information Criterion (AIC) in a stepwise selection procedure to select the best fitting model, distinguishing students that chose STEM from those that chose another (non-STEM) program. For a full discussion on the AIC method, we refer to Burnham and Anderson (2002). From a set of all possible models with all possible predictors, the stepwise procedure selected the best fitting one with the lowest AIC. This procedure rewards models with the least chance of information loss, but penalizes models that use too many predictors. The AIC stepwise methodology has a number of advantages over classic stepwise regression. AIC does not use statistical testing as a criterion for model selection and does not depend on when variables enter the equation as all possible models are considered. Through a leave-one-out, prediction-focused mechanism, this methodology also benefits from cross-validation. Cross-validation allows us to make validated predictions on cross-sectional data, by splitting datasets into independent training data and test data. After selecting the best fitting model, we performed a logistic regression with STEM study choice as dependent variable and the variables from the selected model as predictors. We also reported two additional measures of pseudo - explained variance (deviance) concerning the individual main effects to estimate their specific contribution towards STEM study choice prediction and as control variables for the effects of interest fit. First, individual explained variance indicates how much variance the predictor explains if there are no other predictors present in the model. Second, unique explained variance indicates how much explained variance is lost if the predictor is removed from the model. To conclude, we constructed a ROC curve (receiver operating characteristic curve) indicating how well our model succeeds in profiling STEM students and distinguishing them from their non-STEM colleagues. A ROC curve balances sensitivity and specificity. Sensitivity indicates the proportion of STEM students that were actually classified as STEM students by our STEM choice model, while specificity indicates the non-STEM students that were indeed classified as non-STEM students. A rising sensitivity results in a falling specificity and vice versa. Finally, the *Area Under the Curve* (AUC) indicates how well the model can make the distinction between STEM and non-STEM students. An AUC of 1 indicates perfect accuracy (i.e., a full distinction between STEM and non-STEM choice), while an AUC of .5 indicates a model that cannot make the distinction above chance level. As a rule of thumb, Hosmer and Lemeshow (2000) suggest that AUC coefficients of 0.70 to 0.80 are acceptable, 0.80 to 0.90 are excellent and 0.9 or above are outstanding. For a full discussion on AUC, we refer to Fawcett (2006).

To test Hypothesis 3 (H3), we used a Welch two-sample, two-tailed t-test. Effect sizes are calculated using a Cohen's *d* (Sawilowsky, 2009) and a relative percentage (relative *d*). Cohen's *d* effect size indications are interpreted as follows: 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 (Sawilowski, 2009). The relative *d* percentage is calculated through dividing the highest value by the lowest value, subtracting 1 from that result and then multiplying by 100. Negative effect sizes indicate a higher value for female students. H3 is tested in both the STEM population and the general student population. Apart from this hypothesis, we also analyzed the gender differences in all RIASEC dimensions and STEM preparation to be able to integrate our findings into literature.

Results

Preliminary Analyses

Table 1 shows the proportions of male and female students in the total population, the population of STEM students, and the population of non-STEM students. The chi-squared test on these proportions was significant, χ^2 (1) = 405.62, $p < .001$, rejecting the null hypothesis and indicating male overrepresentation in STEM study fields. Indeed, 54% of all STEM students was male, with only 29% of the female students making a STEM choice, compared to 51% of the male students.

Tables 2 (STEM student population) and 3 (general student population) report the descriptive statistics and the gender differences for the RIASEC interest scores and STEM preparation. Female students show higher social and artistic interests, while male students show higher realistic, enterprising and conventional interests. Female students also show lower investigative interests in the general population, but higher investigative interests in the STEM population. Finally, Tables 2 and 3 also show that female students have a less thorough STEM preparation in secondary education.

We performed a logistic regression on the final STEM study choice model after the AIC procedure to estimate the main and interactive effects of the remaining predictors. Note that adding the main effect of gender to the regression rendered a positive effect for female students towards STEM study choice ($\beta = .78$, $p < .001$), in contrast to the main negative effect of gender on STEM study choice without any other predictors present ($\beta = -.53$, $p < .001$). Three gender-interest interactions (student gender × realistic dimension, student gender × artistic dimension and student gender × enterprising dimension) were removed by the AIC stepwise regression as they did not add to the prediction of STEM study choice. The student gender main effect does not reach significance any more ($p = .15$), indicating that the gender effect in making a STEM study choice is fully explained through the included interaction effects of gender. This null result also indicates that all relevant gender interactions have been added to the regression, providing a conservative control for the effects present.

As the validity of the hypothesis testing is highly dependent on the ability of our STEM study choice model to distinguish STEM and non-STEM students, we plotted the balance between sensitivity and specificity of the model on a ROC curve in Figure 2. Our STEM study choice model manages to correctly identify 87% of the students that indeed chose a STEM program (sensitivity), while it also manages to correctly identify 87% of the students that chose a non-STEM program (specificity). Finally, analyses also revealed an AUC of .94 with an asymptotic 95% CI of [.938, .947], indicating an outstanding fit.

Hypothesis Testing

H1 stated that STEM fit predicts STEM study choice. The final STEM study choice model in Table 4 shows that STEM fit indeed has a significant effect on STEM study choice, even when controlling for the significant effects of gender, STEM preparation and the individual RIASEC dimensions. As an indication of effect size, Table 5 shows that STEM fit has a high individual explained variance, second to STEM preparation only. STEM fit also shows a minor unique explained variance. As STEM fit is a composite measure including all RIASEC dimensions, the unique explained variance thus indicates that STEM fit still has incremental validity above and beyond the effects of individual RIASEC dimensions.

H2 stated that the effect of STEM fit on STEM study choice is moderated by gender, with a stronger effect in female students. Table 4 shows a significant negative parameter estimate for the interaction between STEM fit and gender, while controlling for all other gender interactions. In other words, a better STEM fit will lead to a higher chance for a STEM study choice in female students. Table 4 further shows that female STEM choice is also less determined by STEM preparation, while showing an even more pronounced positive effect of higher investigative interests and a less negative effect of higher social and conventional interests.

H3 stated that female STEM students have a better program fit with their program of choice compared to male students. As such, we tested the difference in specific program fit between male students (M = 85.95, SD = 49.54) and female students (M = 79.88, SD = 50.91) in the STEM population. The result showed a significant effect, t (3387) = 3.51, p < .001, Cohen's d = 0.12, relative d = 8%. Female students indeed showed a better fit with their STEM program compared to male students. To explore if this gender effect generalized to non-STEM programs, we also tested the difference in program fit between male students (M = 90.37, SD = 49.09) and female students (M = 82.00, SD = 47.54) in the full dataset (STEM and non-STEM programs).

The result again showed a significantly better program fit for females, t (7786.83) = 8.12, p < .001, Cohen's d = 0.17, relative d = 10%.

Discussion

Industrialized regions around the globe have experienced increasing difficulty to fill STEM vacancies due to a decline in students who actively enroll for a STEM program in higher education (Ainley et al., 2008; Perera & McIlveen, 2018). Also, there seems to exist a widening gender gap, indicating that women are becoming even more underrepresented in the STEM field (UNESCO, 2016; Xu, 2008). To ensure a steady stream of (female) students into higher education, literature benefits from identifying determinants of STEM study choice, so that education policy and counseling can act upon this knowledge to attract more (female) students. In this context, the present study focused on two research goals. First, we investigated how PE interest fit contributes to the prediction of STEM study choice, with particular consideration towards gender interaction effects. And second, we also investigated whether and to which extent male and female students differed regarding PE interest fit with their specific STEM program. To integrate our findings into literature, we again make use of the leveled framework of differential gender patterns in STEM study choice by Yazilitas and colleagues (2013).

Findings and Theoretical Implications

Regarding our first research question, the present study found that PE interest fit indeed predicted a STEM study choice as STEM students had a better PE interest fit with the STEM field compared to non-STEM students. This effect of PE interest fit is quite robust as the effect is found while controlling for the six individual RIASEC dimensions and STEM preparation. In addition, a STEM student also showed higher realistic and investigative interests and lower artistic, social, enterprising and conventional interests. Finally, a STEM student also enjoyed a more thorough STEM preparation in high school. These findings are commonly observed in literature. First, interest fit is already known to predict study choice (Schelfhout et al., 2019). Second, literature already shows that a student choosing STEM has a high realistic and investigative interest (Su et al., 2009; Su & Rounds, 2015). And finally, literature also shows that a student choosing STEM has had a more thorough STEM preparation, especially through an extensive exposure to mathematics and science (Bagiati et al., 2010; Blackburn, 2017; Bybee, & Fuchs, 2006; Dejarnette, 2012; Wang, 2013a; Wang, 2013b).

Also regarding our first research question, the present study found that this predictive effect of interest fit on STEM study choice was stronger in female students, again while controlling for other possible gender interaction effects. In addition, STEM study choice in female students showed a more pronounced positive effect of high investigative interests and a less negative effect of high social and conventional interests compared to male students. These results are in line with S(C)CT and self-efficacy theory at the micro-level of psychological constructs (Bandura, 2001; Lent, 1994; Lent & Brown, 2019; Lent et al., 2008; Lent et al., 2011; Stajkovic & Luthans, 1998a; Stajkovic & Luthans, 1998b). According to these theories, student self-belief that a study choice is a good fit with personal vocational interests is a necessary condition to make an appropriate STEM study choice. Such a self-belief assumes that a student has sufficient explicit knowledge about his or her own interests and the STEM field to begin with. Literature already shows that female students thus seem to make more and better use of explicit knowledge about their vocational interests and how these interests fit their study choice (Germeijs & Verschueren, 2006; Preston et al., 2007). As the present study shows, female students with a good STEM fit should therefore also have an even higher chance of ultimately choosing a STEM program as female students explicitly use more interest information in their study choice process.

As an answer to our second research question, this stronger female interest fit effect manifests itself also at the more specific program level. Indeed, female STEM students had an 8% better fit with their specific program compared to their male colleagues. Moreover, this effect was also present in the general student population, where female students demonstrated a 10% better interest fit with their specific programs compared to their male colleagues. The present study thus suggests that this gender difference in PE interest fit is not unique to the STEM environment, as it generalizes across all study programs. This generalization further corroborates the reports in literature that female students make more and better use of explicit knowledge like vocational interests in the process of study choice (Germeijs & Verschueren, 2006; Preston et al., 2007).

Previous to the present study, literature primarily determined a good STEM field fit by looking at RIASEC profiles within the STEM field (Perera & McIlveen, 2018; Su & Rounds, 2015; Su et al., 2009). In the present study we have added to literature by determining how an individual's vocational interests can explain making a STEM choice over a non-STEM choice. For this purpose, study programs were marked as either a STEM choice or a non-STEM choice using the UNESCO (2016) definition. Interestingly, the mapping of all study programs in two-dimensional interest space clearly showed an empirical difference in orientation between STEM programs and non-STEM programs, with STEM programs all showing a things/data quadrant orientation. When predicting STEM study choice specifically, the constructed model further integrated the main and gender interaction effects of the individual RIASEC dimensions, STEM fit and STEM preparation. The model performed adequately, by explaining up to 71% of the variance in (non-) STEM study choice. Only 5% of the variance was uniquely explained by specific STEM preparation (i.e., mathematics). These findings indicate that STEM study choice can be largely understood through a vocational interests perspective, without inclusion of cognitive variables. The model also succeeded in profiling STEM and non-STEM students by correctly identifying their (non-) STEM study choice in 87% of all cases. These numbers are on the very high end when compared to known (vocational) literature on study choice (Burns, 2014; Donnay, 1997; Päßler & Hell, 2012). Moreover, the model seemed quite robust against information loss. Indeed, all predictors had low unique explained variance, ranging from about 1 to 5%. As such, little information is lost when a single predictor is removed. Also important, a STEM study choice is predicted by both strong interests (i.e., realistic and investigative dimensions) as well as the relative absence of interests (i.e., artistic, social, enterprising and conventional dimensions). These findings are in line with Holland's theory, as Holland himself always advocated the use of the full profile (Holland, 1997).

At the societal macro-level, we have replicated the result that a STEM study choice in female students is less determined by STEM preparation (Buchmann, 2008; Nix et al., 2015, Vaarmets, 2018; Wang, 2013a; Wang, 2013b). As a plausible explanation and in line with literature, we suspect that this gender interaction is an emanation of a societal effect, installed as early as childhood (Bagiati et al., 2010; Blackburn, 2017; Bybee, & Fuchs, 2006; Dejarnette, 2012) and endorsed up until the end of secondary education (Nix et al., 2015; Sadler et al., 2012; UNESCO, 2016). Indeed, the present study indicated that the minority of female students who still benefit from a thorough STEM preparation at the end of secondary education, seem less inclined to choose a STEM study program in higher education than their male colleagues.

At the institutional level, we thus observe a STEM gender gap in our data, characterized by a male overrepresentation. Only a minority of female students made a STEM study choice

(29%), in contrast to about half of the male students. Gender explained up to 6% of student (non-) STEM choice. As a result, the STEM study field consisted of 46% female students. However, our study did include 60% female students to begin with, somewhat creating a more balanced population composition compared to literature (UNESCO, 2016; Xu, 2008). Taken together, the relatively small proportion of female students choosing STEM seems to be in line with the results from the broader STEM gender gap presented by Stoet and Geary (2018) for developed, progressive and gender-aware countries. As a possible explanation, our open access higher education environment in a developed, progressive and gender-aware country invites students to choose according to their interests. This explanation is endorsed by the good fit of our STEM study choice model, as vocational interests can explain about two-thirds of the variance in STEM study choice for both male and female students, with only a very minor incremental gender-specific effect of about 1%.

Practical Implications

In higher education, a good interest fit predicts study success and persistence (Burns, 2014; Donnay, 1997; Päßler & Hell, 2012; Nye et al., 2012; Rounds & Su, 2014; Schelfhout et al., 2021; Schelfhout et al., 2019). In other words, students that fit their study choice have a higher chance of graduating. As interests are stable constructs (Low et al., 2005), graduated STEM students that have a good fit with the STEM field should have a greater chance to stay in the STEM field for longer periods of time. However, more research is needed to explore this assumption. For instance, longitudinal research should investigate how a good PE interest fit with the STEM field in higher education affects important variables like performance and retention in future STEM work careers. Such longitudinal research should also take special care towards female workers as the determinants of persistence and performance could be different for male and female STEM workers, somewhat similar to higher education STEM study choice (Yazilitas et al., 2013).

Interest fit and STEM preparation are also related to other important predictors of (study) choice such as self-efficacy (Bandura, 2001; Germeijs & Verschueren, 2006; Lent & Brown, 2019). Orientation efforts and research could therefore be directed at further enhancing female awareness of STEM interests and strengthening female self-belief in STEM talent from as early as primary school (Bagiati et al., 2010; Blackburn, 2017; Bybee, & Fuchs, 2006; Dejarnette, 2012). These efforts of boosting self-efficacy beliefs regarding vocational interests and STEM talent should be continued, monitored and stimulated throughout high school (Buchmann, 2008; Nix et al., 2015, Vaarmets, 2018; Wang, 2013a; Wang, 2013b). Towards higher education specifically, education policy can facilitate an active search for female students with an overall STEM fitting interest profile. Study counseling can also make these students explicitly aware of their own interests and the program specific possibilities towards a STEM career. Especially for female students, study orientation focusing on interest fit with the STEM field can widen the pipeline towards the STEM work field. The benefit from this more consistent work force influx can prove important to the economy of industrialized countries (World Economic Forum, 2016).

Limitations

There are two limitations to our study that have to be acknowledged. First, we acknowledge the cross-sectional nature of the present study’s data on first year students. Data with a cross-sectional nature are usually less optimal to investigate research questions that touch upon prediction of future behavior like study choice as causality becomes harder to infer. As interests are stable constructs (Low et al., 2005) and literature already presents strong evidence regarding the predictive properties of vocational interests towards study choice (Fonteyne, 2017;

Nauta, 2010; Nye et al., 2012), we do not consider the use of cross-sectional data a threat to the validity of the present study's results. Strictly speaking however, predicting study choice in a regression still does not coincide with predicting study choice in actual behavior if both predictors as well as the criterion are questioned at roughly the same time. We therefore opted to use a second, independent data set of former successful and persistent students to construct the program RIASEC profiles by using these former students as incumbents (Allen & Robbins, 2010; Schelfhout et al., 2019; Schelfhout et al., 2021). For the present study, student PE interest fit is therefore determined by comparing the data of incoming students to the data of former senior students. As these datasets were obtained independently of each other at different times, the interest profiles of former successful students within and beyond the STEM field predict which profiles the incoming students will exhibit as similar environments attract similar students (Schelfhout et al., 2019). The results of the present study again confirmed this effect as incoming STEM students had a better fit with the STEM field (i.e., more similarity to former STEM students) than incoming non-STEM students. Additionally, the present study was also conducted on quite a large data sample, across all faculties and programs of a large university (Shanghai top 100), thus covering a wide range of (non-) STEM study topics. The use of 39 largely independent subsamples (i.e., study programs) with different student populations can further overcome the limitations of a cross-sectional design towards prediction, especially because the AIC procedure uses a built-in, leave-one-out cross-validation mechanism. Such a mechanism allows us to make predictions on cross-sectional data by splitting the data into independent training and test samples. The already discussed robustness of our STEM prediction model further corroborates the validity of this methodology.

Second, we also acknowledge the uniqueness of Belgian open access higher education compared to the more closed access education systems elsewhere in the world. However, such an open access context with less options for customization (e.g., changing majors is not possible) does allow assessing the effects of vocational interests without additional constraints that are imposed in systems that use high stakes tests or entrance requirements. Future research therefore has to investigate if the effects found in the present study can be replicated in other educational systems, with more restricted access.

Conclusion

A student making a STEM choice in an open access study environment has a good interest fit with the STEM field, has a specific RIASEC profile (i.e., with higher realistic and investigative interest and lower artistic, social, enterprising and conventional interests) and has enjoyed a more thorough STEM preparation in high school. For female students specifically, the effect of this good PE interest fit is even more pronounced, while the effect of STEM preparation diminishes. Female STEM choice also shows more pronounced positive effects of investigative interests and less negative effects of high social and conventional interests. Finally, following a (non-) STEM choice, female students fit their specific (STEM) study program better than their male colleagues. In order to promote STEM enrolment and address the gender gap, education policy can facilitate the search for female students with an overall STEM fitting interest profile. Study counseling can make these students explicitly aware of their own interests and the (program specific) possibilities towards a STEM career.

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Tables

Table 1

Student Gender and STEM Choice Cross-Tabulation

		STEM choice		total
		0	1	
Males	N_m	1,879	1,828	3,707
	% within student gender	51	49	100
	% within STEM choice	33	54	40
Females	N_f	3,894	1,561	5,455
	% within student gender	71	29	100
	% within STEM choice	67	46	60
Total	N	5,773	3,389	9,162

Note. STEM = Science, Technology, Engineering, Mathematics. 0 = non-STEM choice, 1 = STEM choice.

Table 2

Student Gender Differences in the STEM Student Population

Student interests and STEM preparation	*n*	*M*	M_m	M_f	*SD*	Cohen's *d*	Relative *d*
Realistic dimension	3,389	33.79	45.94	19.56	26.96	1.13	135%
Investigative dimension	3,389	44.88	41.94	48.33	20.96	-0.31	-15%
Artistic dimension	3,389	23.38	20.46	26.80	22.52	-0.28	-24%
Social dimension	3,389	22.67	15.21	31.40	21.50	-0.80	-106%
Enterprising dimension	3,389	23.32	25.95	20.23	22.47	0.26	28%
Conventional dimension	3,389	17.49	18.49	16.32	19.24	0.11	13%
STEM preparation	3,377	6.11	6.42	5.75	1.51	0.45	12%

Note. STEM = Science, Technology, Engineering, Mathematics. M_m = male student average and M_f = female student average. STEM preparation was operationalized through the hours of mathematics students chose in the final two years of high school up to a maximum of eight. The RIASEC dimensions were measured on a scale from 1 to 100. Cohen's *d* effect size rules of thumb (Sawilowski, 2009): 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. The relative *d* percentage is calculated through dividing the highest value by the lowest value, subtracting 1 from that result and then multiplying by 100. Negative effect sizes indicate a higher value for female students. All gender differences were significant at the level $p < .001$.

Table 3

Student Gender Differences in the General Student Population

Student interests and STEM preparation	*N*	*M*	M_m	M_f	*SD*	Cohen's *d*	Relative *d*
Realistic dimension	9,162	18.86	32.00	9.93	23.61	1.00	222%
Investigative dimension	9,162	33.5	34.48	32.83	21.29	0.08	5%
Artistic dimension	9,162	29.95	24.62	33.57	25.59	-0.36	-36%
Social dimension	9,162	34.93	22.7	43.23	25.9	-0.88	-90%
Enterprising dimension	9,162	33.45	37.23	30.87	28.17	0.23	21%
Conventional dimension	9,162	21.08	25.08	18.36	22.86	0.29	37%
STEM preparation	9,135	4.95	5.41	4.59	2.88	0.47	18%

Note. STEM = Science, Technology, Engineering, Mathematics. M_m = male student average and M_f = female student average. STEM preparation was operationalized through the hours of mathematics students chose in the final two years of high school up to a maximum of eight. The RIASEC dimensions were measured on a scale from 1 to 100. Cohen's *d* effect size rules of thumb (Sawilowski, 2009): 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. A negative effect size indicates higher female student scores. The relative *d* percentage is calculated through dividing the highest value by the lowest value, subtracting 1 from that result and then multiplying by 100. Negative effect sizes indicate a higher value for female students. All gender differences were significant at the level $p < .001$.

Table 4

STEM Study Choice Model: Coefficients

Coefficients	Estimate	*z*-statistic
(Intercept)	-3.13	-13.38***
Student gender	0.44	1.43
STEM fit	-0.0068	-5.65***
STEM preparation	0.59	16.78***
Realistic dimension	0.049	22.39***
Investigative dimension	0.039	12.70***
Artistic dimension	-0.014	-7.60***
Social dimension	-0.038	-11.26***
Enterprising dimension	-0.013	-6.13***
Conventional dimension	-0.028	-8.09***
Student gender × STEM fit	-0.0053	-3.19**
Student gender × STEM preparation	-0.14	-3.71**
Student gender × Investigative dimension	0.022	5.28***
Student gender × Social dimension	0.015	3.29**
Student gender × Conventional dimension	0.021	5.03***

Note. STEM = Science, Technology, Engineering, Mathematics. The table displays the final model estimate of the logistic regression of STEM study choice (1 = STEM, 0 = non-STEM) on the six RIASEC dimensions of vocational interests, STEM preparation (weekly hours of mathematics in high school) and STEM (interest) fit, with addition of all relevant gender interactions. Student gender is coded 1 for female students and 0 for male students. The model explains about 71% of the (pseudo-) variance through a Nagelkerke's R^2. Note that the sign of the parameter estimate for STEM fit is negative. This negative estimate is due to the nature of Euclidean distance in which a lower score indicates a better fit. $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

Table 5

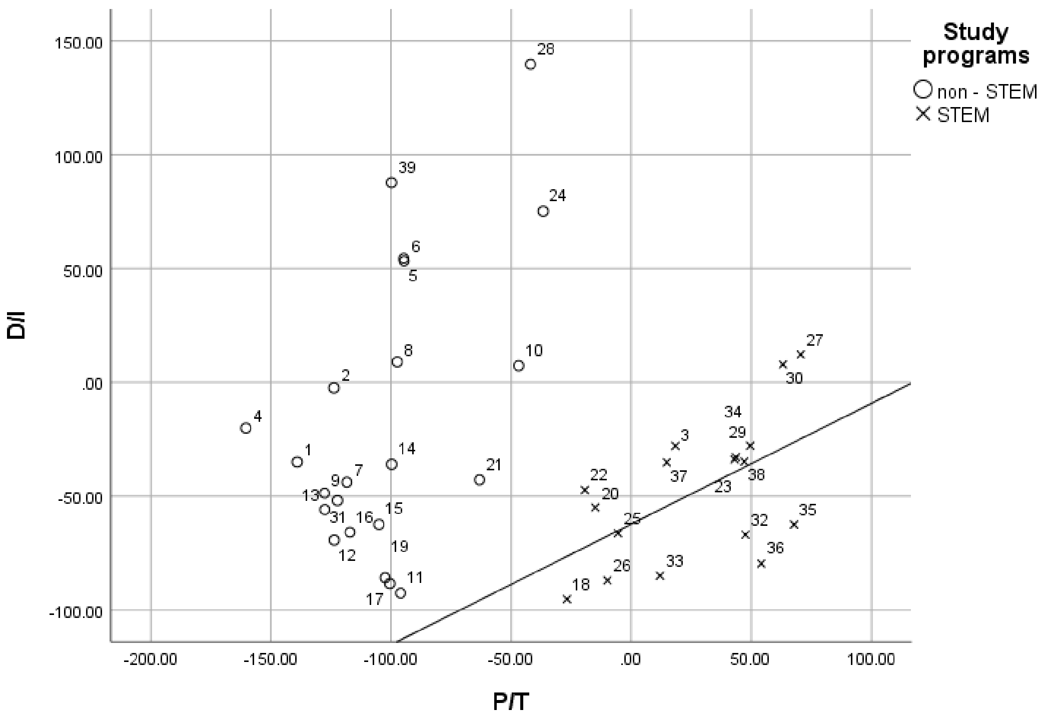
STEM Study Choice Model: Individual and Unique Explained Variance

Predictors	Individual explained variance	Unique explained variance
Student gender	0.06	0.01
STEM fit	0.32	0.01
STEM preparation	0.34	0.05
Realistic dimension	0.30	0.05
Investigative dimension	0.22	0.05
Artistic dimension	0.05	0.01
Social dimension	0.19	0.02
Enterprising dimension	0.11	< 0.01
Conventional dimension	0.02	< 0.01

Note. STEM = Science, Technology, Engineering, Mathematics. The table displays the explained pseudo – variance (deviance) for each predictor of the logistic regression of STEM study choice (1 = STEM, 0 = non-STEM) on the six RIASEC dimensions of vocational interests, STEM preparation, STEM (interest) fit and gender. Individual explained variance indicates how much variance the predictor explains if there are no other predictors present in the model. Unique explained variance indicates how much explained variance is lost if the predictor is removed from the model. Individual and unique explained variance were measured using a Nagelkerke's R^2. All predictors have a somewhat low and thus similar unique explained variance. This result indicates that the model is quite robust. Indeed, information loss remains limited when removing one predictor from the model. In contrast, the individual explained variance over all predictors shows a much wider range. Important to note, the variance measures for gender provide an additional indication of the effect of student gender on STEM study choice. About one to six percent of STEM study choice can be explained through student gender (without gender interactions), while controlling for the other predictors.

Figures

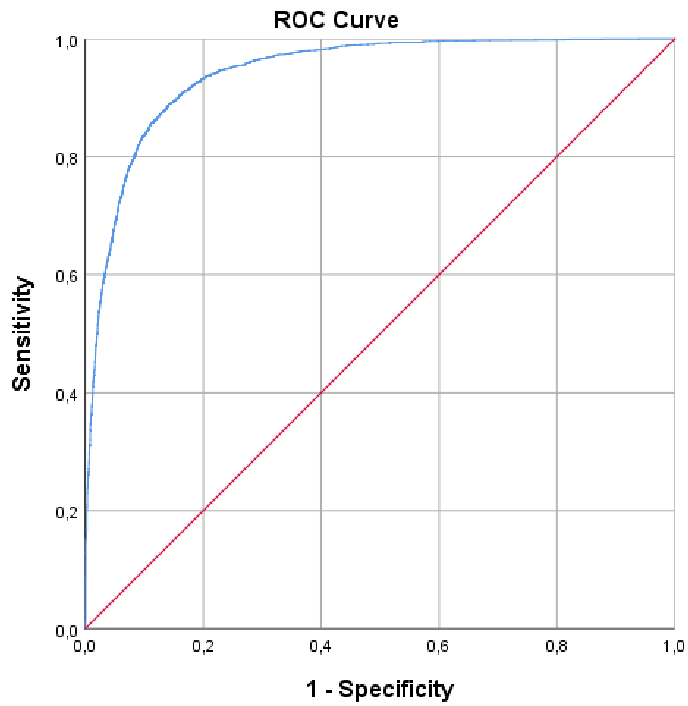
Figure 1. Scatterplot of 39 Programs using the People / Things (X-axis) and Data / Ideas (Y-axis) Dimensions.



Note. The programs included are (in random order): 1 = Psychology (0), 2 = Communication Sciences (0), 3 = Mathematics (1), 4 = Educational Sciences (0), 5 = Political Sciences (0), 6 = Law (0), 7 = Sociology (0), 8 = Criminological Sciences (0), 9 = Speech Language and Hearing Sciences (0), 10 = Physical Education and Movement Sciences (0), 11 = Philosophy (0), 12 = Linguistics and Literature (0), 13 = East European Languages and Cultures (0), 14 = History (0), 15 = Oriental Languages and Cultures (0), 16 = Moral Sciences (0), 17 = Art History (0), 18 = Archaeology (0), 19 = African Studies (0), 20 = Veterinary Medicine (0), 21 = Physical Therapy and Motor Rehabilitation (0), 22 = Pharmaceutical Sciences (0), 23 = Bioscience Engineering (1), 24 = Economics (0), 25 = Biomedical Sciences (1), 26 = Engineering – Architecture (1), 27

= Engineering (1), 28 = Business Economics (0), 29 = Bioscience Engineering Technology (1), 30 = Engineering Technology (1), 31 = Applied Language Studies (0), 32 = Biochemistry and Biotechnology (1), 33 = Biology (1), 34 = Chemistry (1), 35 = Physics and Astronomy (1), 36 = Geology (1), 37 = Geography and Geomatics (1), 38 = Computer Sciences (1), 39 = Public Administration and Management (0). All STEM programs are located in the right lower corner (things/data quadrant). The reference line, $y = 0.53x - 62.20$, indicates the relation between the P/T and D/I coordinates of the STEM programs, with an explained variance of 31%.

Figure 2. The ROC Curve of STEM Study Choice versus non-STEM Study Choice.



Note. Sensitivity indicates the proportion of STEM students that were actually classified as STEM students by our STEM choice model. Specificity indicates the non-STEM students that were indeed classified as non-STEM students. A rising sensitivity results in a falling specificity and vice versa. The blue ROC curve delineates the *Area Under the Curve* (AUC = .94) and indicates how well the model distinguishes STEM and non-STEM students. The reference line is indicated in red and represents the 50% chance level benchmark of distinction.