Academic specialization choices and academic achievement
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1 Introduction

Each year about 30,000 students decide to enrol in Dutch university education (see, e.g., Statistics Netherlands [CBS], 2000). These students choose different specializations, such as law, psychology, history, and so on. Moreover, they vary widely in achievements within their chosen specialization. This dissertation reports studies on students’ specialization choice, and on the factors which influence students’ achievements.

1.1 University students’ specialization choice

In the social sciences, the choice of an academic specialization of college and university students has been studied extensively. In psychology, these choices are usually explained by students’ vocational interests (see, e.g., Holland, 1997). In that context, students choose an academic specialization that has a study content that best fits their interests. Students who are interested in language and culture study linguistics, and students who are interested in physical processes study physics. In the economics of education, financial benefits are commonly brought forward to explain the choice of an academic specialization (see, e.g., Vella & Gregory, 1996). In that setting, students choose an academic specialization that leads to the career that gives them maximum earnings. Both students who choose linguistics and students who choose physics know that, linguistics and physics, respectively, are the specializations that will avail them most earnings.

In both theories, it is assumed that students have desires, which must be fulfilled when choosing a specialization. Students are faced with a set of alternative academic specializations. They have perceptions of characteristics, or attributes, of these specializations. The alternative with the perceived attributes that best meets their desires is chosen. In other words, students choose the specialization from which they gain most, either from a psychological, or an economic viewpoint. Therefore, things that a student can desire, and which a specialization can provide are called benefits in this thesis.

In psychology, benefits of academic specializations are associated with study content, and in economics they are associated with monetary returns. It may be argued that each of these fields gives a limited view of reality; both theories are associated with only one sort of benefit. It is very likely that students consider both income and study content when making an academic choice. Each kind of benefit may be compensated by the other. For example, a history student may sacrifice some of her future income for a very interesting study content, whereas an
economics student may sacrifice interesting study content for high future income. In addition, it may be argued that study content and monetary income nonetheless are a somewhat restricted set of benefits. Other benefits need to be considered to give a better explanation of students’ choices. For example, some specializations, like medicine and psychology, are directed towards helping other people. It is very likely that students choose these specializations because they feel the need to help others. Another example is the effort a specialization requires. Not every specialization demands as much from a student. Some specializations are more difficult than others, or may demand more study time. Presumably, students take into account these demands when choosing a specialization. It seems plausible that some students like putting effort at their study whereas other students do not.

When both students’ desires and perceptions of academic specializations are assessed for this broader set of benefits, at least three questions may be asked. The first question is what sorts of desires do students from different academic specializations typically have when choosing an academic specialization. For example, do students who choose economics deem the study content of their future specialization equally important as students who choose history? Do students who choose English linguistics want to put as much effort at their specialization as do students who choose medical science?

The second question is whether perceptions of specific specializations are similar for students who choose different specializations. For example, does a student who chooses economics view the study content of economics as equally interesting as students who choose another specialization? Do students who choose medicine perceive medicine as equally meaningful to others as students who choose other specializations?

The third question is whether the assessments of students on, respectively, their desires associated with specializations in general, and their perceptions of benefits of specific academic specializations, can be used to distinguish between students who choose different specializations. In other words, can they be used in prediction studies to give accurate predictions of the specialization students actually choose.

1.2 University students’ academic achievement

The academic achievement of students in higher education has been studied extensively. Many variables have been used to predict academic achievement. The predictor that has most often been used is intelligence. However, in the Dutch situation the relation with academic achievement has been reported to be very small (see, e.g., Busato, Prins, Elshout, & Hamaker, 2000). This is commonly attributed to restriction of range (see, e.g., Busato, 1998). Students entering Dutch university education are mostly members of a highly selective group who completed pre-university education. Some researchers have stressed the achievement in previous education, commonly measured by school grades. Others have emphasized the importance of personality traits. For example, students scoring high on
conscientiousness have been reported to have higher academic achievement (see, e.g., Wolfe & Johnson, 1995). Another variable that has often been associated with academic achievement is motivation. Students who are more motivated are commonly said to perform better (see, e.g., Waters & Waters, 1976). Sometimes, low academic achievement is attributed to bad study skills. Other researchers attributed academic achievement to students' belief in their ability to perform academic tasks (see, e.g., Kleijn, van der Ploeg, & Topman, 1994).

The afore mentioned examples of predictors are all psychological variables. Many non-psychological variables have been used to explain academic achievement as well. Basic personal characteristics such as gender and age have been used. For example, female students have been said to perform better than their male colleagues in many courses (see, e.g., Mau & Lynn, 2001). Another approach that has been taken is studying the time students allocate to several activities, such as sleeping, working, and studying. For example, it has been shown that time spent on studying is not always positively associated with academic achievement (Olivares, 2002). Sometimes, academic achievement has been linked to students' financial situation. Students with performance-related grants are said to make more study progress. Moreover, students who expect more financial returns from their specialization have been found to have higher probabilities to persist in their study (see, e.g., Oosterbeek & Webbink, 1995).

Frequently, the validity of predictors of academic achievement is studied in one specific academic discipline. Studies that consider the predictive validity of variables in more than one specialization are scarce. Nevertheless, very often research outcomes are generalized to all students in higher education. Many of these generalizations may not be legitimate. It seems very plausible that the relationships between predictors and academic achievement are not invariant across different academic specializations. These differences may result from two sources. First, the curriculum of the specializations is different, and therefore the personal attributes that are optimal for high academic achievement are also different. Second, different academic specializations attract different sorts of students. For example, economics students and history students have different interests and motives.

1.3 Missing data

In prediction studies, missing values are often encountered. Missing values can emerge as a result of many different processes. For example, in surveys that ask students to report their parents' income, a sizeable fraction of the respondents typically refuses to answer. In psychological tests, some of the questions are often inadvertently skipped. Some of the students who have to report their expected income after graduation do not know what to answer and skip the question. Another example of missing data that is often encountered in educational research are the grade records containing grades obtained on a set of courses that differ in content from student to student. This missingness is the result of a choice process. Each student can only take examinations in a set of subjects, and, therefore, not
all grades are available. These examples of missing data are all cases in which the missingness is beyond the researcher's control; they are an unpleasant result of data collection. In contrast, missing data can also be under the control of the researcher. When data are not intended to be collected, data are planned missing. It has been shown that surveys with longer questionnaires, which increase the respondent's burden, tend to have higher non response (see, e.g., Dillman, Sinclair, & Clark, 1993). Therefore, in prediction studies in which many different variables are used, it is convenient to use multiple questionnaire booklets with different subsets of items. The booklets contain less items than the total item set. Consequently, the response rate will be higher than when using questionnaires that contain all items. Missing data are no longer only a burden, but can also be used as a way to increase response rates.

Both planned and unplanned missing data need to be dealt with. Methods for missing data have been developed ranging from very simple to highly advanced. An example of very simple missing data methods is personal mean imputation, which replaces a missing value with the personal average on relevant variables for which a person has available data. At least implicitly, this personal mean has often been used. In calculating the Grade Point Average (GPA), the average grade for subjects that a student has taken is implicitly substituted for non-taken subjects in grade records. An example of a very advanced method of handling missing values is Data Augmentation (DA) (see, e.g., Schafer, 1997, 1998). DA imputes missing values in a regression sort of way: missing values are predicted using the observed values. Compared to simpler missing data methods, DA takes into account the uncertainty that is a natural result of missing values. Moreover, advanced procedures, such as Schafer's NORM (1997, 1998), have been shown to give very accurate estimates of missing values.

The mechanisms that underly the missing data can be divided into ignorable and nonignorable missingness. Missing values are ignorable if their missingness does not depend on the values of the missing data (see, e.g., Schafer & Graham, 2002). If the missingness depends on the data that are missing, then the data are called nonignorable. Only when missing data are ignorable, missing values can be estimated using the available values. For example, if a respondent accidentally skips an item of a personality test, the missingness does not depend on the score he or she would have given, and therefore the missingness is ignorable. However, when students choose not to take examinations in mathematics because their expected performance would be low, the missingness does depend on the missing grade, and therefore the unavailable grades in mathematics are nonignorable.

Missing data methods differ to a large extent in the assumptions they have concerning the mechanism that underly the missing data. Generally speaking, advanced methods such as DA assume that missing data are ignorable, whereas simple methods (implicitly) make stricter assumptions. For that, and other reasons, advanced methods should be generally preferred over simple methods. It should be noted that ignorability is usually not known to hold, but it must be assumed. When replacing skipped items in a questionnaire with methods like DA, it is assumed that items were skipped unintentionally so that they are ignorable.
1.4 Overview of the chapters

Sometimes ignorability is known to hold. Planned missing data are by definition ignorable (see, e.g., Schafer & Graham, 2002). Especially in survey research the efficiency of missing data methods in estimating planned missing data has been studied. Several researchers such as Graham, Hofer, and MacKinnon (1996), applied advanced missing data techniques to survey questionnaires that had items missing by design, and concluded that the missing data could be retrieved satisfactorily.

When studying the academic behavior of students in higher education, measurement instruments are often used, and data are often gathered using paper and pencil questionnaires. For that situation it also seems appealing to apply incomplete designs in order to gather as many information from as many respondents as possible. When developing measurement instruments, two different strategies are commonly applied. First, the instrument is constructed to be valid for predicting a given criterion. Second, the instrument is constructed to be a precise measurement of some attribute of an individual. Lord and Novick (1968), and others showed that both goals can not be optimized at the same time. In other words, it is impossible to simultaneously maximize both measurement precision, and predictive validity. If measurement precision is maximized, predictive validity tends to be lower. If predictive validity is maximized, measurement precision tends to be lower. This conflict between measurement and prediction should also be considered, when incomplete designs are applied to measurement instruments in prediction studies. The different missing data techniques that are at hand to estimate missing item responses seem to maximize only one of these two goals, at the expense of the other. Therefore, these methods need to be compared on their performance at reconstructing the reliability and predictive validity of tests with planned missing items.

1.4 Overview of the chapters

This thesis discusses the prediction of two outcomes of university student behavior: students’ specialization choice, and students’ academic achievement. However, missing data are often encountered in prediction studies. These missing values are an unpleasant result of collecting data, and need to be dealt with. Moreover, missing data can be planned, and as such be used as a way to increase response rates in surveys. Therefore, in order to properly deal with missing values in prediction studies, missing data methods are studied first.

In chapter 2, GPA is considered a missing data technique for unavailable grades in school grade records. It is studied what alternative methods for handling unavailable school grades can best be used in future studies on academic achievement. To that end, theoretical and empirical differences between GPA and seven alternative missing grade techniques are considered. In addition, the completed grade records (observed and imputed values) are used in two prediction of academic achievement analyses, to study what method produces best predictions of academic achievement.
Chapter 3 discusses planned missing data, and the measurement-prediction paradox. A simulation study is performed in which psychological paper and pencil test are simulated, and a third part of the item responses is made unobservable using an incomplete test design. Next, several missing data techniques are compared on their performance at reconstructing total scores, test reliability and predictive validity.

Chapter 4 considers the usefulness of four predictive blocks to predict academic achievement. These four blocks comprise background, economic, time budget, and psychological variables. Data are collected using a survey. An incomplete test design is applied to the psychological scales of this survey resulting in three questionnaire forms. Of the psychological scales, two thirds of the items are administered to each respondent. The missing third part is estimated with a missing data procedure NORM, which gave good results in the simulation study of chapter 3. The four blocks are compared on their predictive power, and the stability of their predictions. In addition, it is checked whether the predictive blocks behave similarly in different academic specializations.

In chapter 5, both economic and psychological theory are used to derive predictors of university students’ discipline choice. From economics the idea of utility maximization is employed. Using psychological theory, non-monetary profits of education are made explicit. Freshmen of nine different university disciplines are assessed at their desires associated with 13 benefits of academic specializations. These desires are used to predict actual academic specialization choices. The missing values that are a result of skipping items are estimated with missing data procedure NORM.

In chapter 6, the set of benefits introduced in chapter 5 is employed again. In addition to the desires students express with respect to these benefits, perceptions of the benefits of four academic specializations are assessed. Five methods – discriminant analysis, the Conditional Logit Model (CLM), Multi-Attribute Utility Theory (MAUT), Equally Weighted Criteria (EWC), and the Euclidean distance – are applied to predict academic specialization choice. These five methods make a different use of these two sorts of variables to predict specialization choice. Missing values that are a result of students skipping items are estimated with missing data procedure NORM.

In chapter 7, it is noted that two of the methods that are used in chapter 6 – CLM and MAUT – are theoretically very similar. Both methods make use of specialization-specific evaluations of attributes. First, theoretical similarities and dissimilarities of the two methods are discussed. Second, it is verified whether both methods yield similar results when they are used to predict the specialization choices of two cohorts of university freshmen.

Finally, in chapter 8 an overview and conclusions of this dissertation are given.