Chapter 12

Investigating students' ability to transfer mathematics

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It is a fundamental, if implicit, assumption of the modern day education system that students possess the ability to transfer the skills and knowledge learnt in a particular context to a different context. However, there has been much debate amongst researchers regarding factors that affect the occurrence of transfer. The nature of transfer, and the type of transfer that occurs in different contexts, have been examined and debated for at least a century (see Barnett & Ceci, 2002; Rebello et al., 2004) for brief surveys). The importance of transfer cannot be overstated - if knowledge and learning cannot be applied outside the original learning context, they are very limited in usefulness. Transfer has even been described as the 'ultimate goal of education' by some researchers (McKeough, Lupart & Marini, 1995).

The aim of this project was to quantitatively measure the ability of first year science students to use skills and knowledge learned in mathematics courses, in other contexts; specifically science. The ability to transfer mathematics skills into a chosen science discipline is of crucial importance in students' development as scientists, and in their future careers. It is also likely that the findings of this study will contribute more generally to our understanding of transfer involving other areas of university study and, indeed, to the transfer of knowledge and skills gained in the university to new situations that graduates are likely to face.

Transfer of mathematics knowledge and skills

At the University of Sydney, as in many other universities, students of science and engineering are required to study mathematics as a subject in its own right. It is expected that they will be able to use the skills and knowledge acquired from their mathematics courses in other disciplines; that is, that they will be able to transfer their mathematics to other disciplines. Lecturers in these other disciplines typically complain that students either do not have sufficient mathematics or are unable to apply it in context. Such complaints are not new, nor are they restricted to the University of Sydney. In universities across the world there has been a proliferation of courses which teach mathematics 'in context', purportedly as a solution to the problem. Unfortunately, there is little evidence to suggest that such courses solve the problem at all. Gill (1999b) discusses precisely this situation at King's College London, and argues that teaching mathematics in a particular context ties the mathematics to that context and does not improve the situation. Zevenbergen (2001) points to research showing that embedding mathematics in contexts can serve as a distractor for some students, and warns of the difficulties caused by embedding mathematics in word problems.

Clearly, there is no easy solution, and the studies reported in this chapter do not directly address the problem. Rather, they are an attempt to answer the questions:

- To what extent are students able to transfer mathematical skills and knowledge?
- Is there a way to measure transfer ability?

Another question that was investigated concerned the possible linkage between an understanding of graphs, defined as ‘graphicacy’, and success in solving other mathematical problems, noted by Gill (1999a). Gill concluded that there is mathematical understanding related to understanding graphs and slopes that may underpin higher order mathematical concepts. However, he was unable to say whether an integrated understanding of graphs is a result of, or a pre-requisite for, deep mathematical understanding. Answers to questions such as these may be useful in designing strategies to improve transfer.

The research was begun by four academics, one from each of mathematics, physics, microbiology and computer science within the Faculty of Science at the University of Sydney, aided by a research assistant and a BSc(Honours) student, who interacted with students, helped with data handling and participated in generating and testing hypotheses. During the initial stages, an academic from the Institute for Teaching and Learning at the University of Sydney assisted with framing the project and focusing on the process of investigation.

Theoretical background

There have been many studies of ‘generic’ transfer - the type that enables the education of primary school children to be useful and that makes workplace and sporting training worthwhile. In one sense, the obviousness of transfer is such that it does not need to be stated, yet researchers have encountered many difficulties when it comes to describing transfer, either qualitatively or quantitatively. There has been a great deal of research conducted on transfer over the past century and recent work, such as that of Barnett and Ceci (2002), has narrowed the gap between different views of transfer.

Measurements of transfer

Most studies that have attempted to measure transfer have been quantitative only in the sense that the data sets generated were large enough to perform some kind of statistical analysis. But the only studies known to the authors that try to quantify transfer in some way are those that used a pre- and post-test methodology (Hake, 1998; Singley & Anderson, 1989). In these studies, the transfer was measured as a type of gain.

The present study is thought to be unique in the attempt to quantify the degree of transfer of assumed knowledge. Accordingly, a transfer index had to be devised, tested and revised. This process is explained, followed by a description of the analyses that were carried out.

Models of student thinking

There is a large and diverse body of literature in the field of transfer, from both cognitive psychologists and educational scientists, but it is only with the adoption of accepted frameworks for transfer and educational science that helpful debate and comparison of research can be undertaken. Such frameworks, by Barnett and Ceci (2002), Redish (2003), Tuminaro (2004) and Rebello et al. (2004) were applied in this project to interpret our results.

While there are several different models of memory, the framework of dividing memory into *working* (short-term) memory and *long-term* memory was considered useful. Working memory can only handle a small number of data blocks but long-term memory contains vast amounts of information. Transfer of information from working to long-term memory may be difficult and time consuming and requires repetition and time (up to weeks).

Taxonomy for transfer

Due to the diversity of transfer research, it was important to situate this study within a common reference or framework to enable comparisons with different studies and to discuss results. Although acknowledged by its authors as lacking 'sharp edges' (in regard to generating quantitative predictions), Barnett and Ceci's (2002) taxonomy is useful for positioning this project in regard to other work, and in seeing the way forward for future research by those concerned with transfer.

The taxonomy has the following dimensions of context (see Figure 12.1): Knowledge domain; Physical context; Temporal context; Functional context; Social context and Modality. According to these dimensions, the project described in this paper only deals with non-near transfer in the Knowledge Domain, since all the other contexts were the same for the students involved.

Figure 12.1. Barnett and Ceci's (2002) taxonomy for far transfer

A Content: What transferred			
Learned skill	Procedure	Representation	Principle or heuristic
Performance change	Speed	Accuracy	Approach
Memory demands	Execute only	Recognise and execute	Recall, recognise and execute

B Context: When and where transferred from and to					
	Near →				**Far**
Knowledge domain	Mouse vs. rat	Biology vs. botany	Biology vs. economics	Science vs. history	Science vs. art
Physical context	Same room at school	Different room at school	School vs. research lab	School vs. home	School vs. beach
Temporal context	Same session	Next day	Weeks later	Months later	Years later
Functional context	Both clearly academic	Both academic but one non-evaluative	Academic vs. filling in forms	Academic vs. informal questionnaire	Academic vs. at play
Social context	Both individual	Individual vs. pair	Individual vs. small group	Individual vs. large group	Individual vs. society
Modality	Both written, same format	Both written, multiple choice vs. essay	Book learning vs. oral exam	Lecture vs. wine tasting	Lecture vs. wood carving

Measuring ability to transfer mathematics skills and knowledge

The ability to transfer mathematics was quantified by comparing marks obtained for mathematics questions with those obtained for numerical questions that depended on use of the same mathematics knowledge and skills but were set in a scientific context. The marks were analysed to generate a Transfer Rating (Britton, New, Sharma & Yardley, 2005) that expressed the ability of each student to transfer the mathematics knowledge to the scientific questions. Further consideration of the results suggested some improvements to the test instrument and to the method of calculating the transfer ability – leading to production of a Transfer Index that could be used to study correlations between variables affecting performance in science and mathematics subjects.

The first instrument

In order to test the ability of students to transfer mathematical skills and knowledge to other disciplines, we designed an instrument consisting of mathematical questions set in the context of particular scientific disciplines. We wanted each question to contain enough discipline-specific information that it could be answered using mathematical knowledge only, without any previous knowledge of the particular discipline.

The first task was to select a topic or set of concepts taught in first year mathematics that would be used by the different science disciplines after it was taught by the mathematicians. However, due to the diversity in mathematics requirements of introductory science courses it was decided to focus on content taught in senior high school. The topic chosen was exponentials and logarithms, which is covered in the final two years of high school in the Mathematics Higher School Certificate in the state of New South Wales course (NSW Board of Studies, 1997), is assumed knowledge for first year university science and is briefly revised in first year mathematics.

At the outset, two alternatives were considered for the structure of the instrument. The discipline-specific questions could depend on identical mathematical concepts in the same sequence for the different disciplines, or the discipline-specific questions could be taken from the same narrow area of mathematics with no constraints about a one-to-one matching of concepts or sequence. Since the students were initially expected to attempt questions in several different science disciplines, questions written according to the first alternative could be answered using pattern recognition. Hence it was decided to follow the second alternative.

Each researcher wrote several questions that were taken from the same narrow area of mathematics with no constraints about a one-to-one matching of concepts or sequence. The questions were read by others on the team and modified to give maximum comprehensibility and ease of reading and interpretation. The issue of comprehending questions from unfamiliar discipline areas was critical (New, Britton, Sharma & Brew, 2001). Initially, the questions included explanations which were not entirely comprehensible to those who had not written them. It is clearly difficult for academics to correctly gauge the general understanding of their specialist areas when writing background information. The questions went through several cycles of modifications.

As the iterations of the discipline-specific questions converged, the mathematician in the group used the concepts that appeared in the discipline-specific questions to design a series of mathematics questions, which were read by all researchers and modified. The first draft of the instrument contained two questions from each of microbiology and physics, three from computer science and one from mathematics, each question containing several parts. Following a trial of the instrument with higher year students (third year and above) from the participating disciplines, the questions were modified and some sections completely eliminated to give a test that could be realistically expected to be completed within one hour.

The final version of the instrument used with first year students consisted of a physics component based on exponential decay of the number of photons in a photon beam, a microbiology component based on killing bacteria, a computer science component based on Big-Oh notation and a mathematics component which consisted of four straightforward questions. Where possible, the components had a similar structure, so that the application of a particular skill in different contexts could be tested.

The following extracts from the instrument illustrate some parallel components (Figure 12.2).

Physics

Consider a beam of photons with identical energies all travelling in the same direction, head-on into a particular medium. The number of photons which survive as the beam passes through the medium decreases exponentially. The distance over which the number of photons is halved is called the half-thickness of the medium. Let N be the number of photons which have survived at a distance x into the medium, and let g be the half-thickness.

a. If $N(x) = N_0 \times 2^{-kx}$, where N_0 is the initial number of photons, and k is a positive constant, express k in terms of g.

b. Suppose a medium is 10mm thick, with a half-thickness of 0.5 mm, and that 10^{10} photons enter the medium head-on.
Draw a graph of log N against x, with a scale marked on the axes.

Microbiology

The bacterium *Staphylococcus aureus* ('golden staph') found in poultry stuffing is killed by heat. After a quantity of poultry stuffing has been heated to 62°C, the cell concentration of the golden staph bacteria decreases exponentially. The Decimal Reduction Time at 62°C, *D62*, is the length of time required for the cell concentration to decrease to 1/10th of its original value. Let N be the cell concentration of the bacteria at time t minutes after the stuffing has been heated to 62°C.

a. If $N(t) = N_0 \times 10^{-kt}$, where N_0 is the initial cell concentration and k is a positive constant, express k in terms of D_{62}.

b. For golden staph, the decimal reduction time at 62°C, D_{62}, is 8 minutes.
Draw a graph of log N against t if the initial concentration is 10^5 cells/g.

Mathematics

a. If $P = 5e^{kt}$ and $P = 10$ when $t = 3$, find k.

b. If $y = 4e^{-0.1x}$, draw a graph of ln y against x, for $0 \le x \le 10$.

Figure 12.2. Parallel questions in Instrument 1

Administering the instrument. There were several versions of the instrument, with the discipline-specific components in different orders, but with the mathematics components last in every case. Thus a selection of students would start with each discipline-specific component, to ensure a sufficient number of responses to each discipline, and to stop students simply choosing their favourite discipline. This procedure was also designed to lessen the effect of pattern recognition in answering later components based on earlier ones.

The students were told that there were components from the different disciplines and that they should be attempted in the order in which they appeared on the instrument. After answering other components for 50 minutes, all students were asked to do the mathematics component. Student identification numbers were requested so that further analysis could be done, and all students signed Human Ethics Clearance Forms so their student records could be accessed.

Calculating transfer. The student responses to each part of a question were marked using a simple marking scheme - 2 marks for a correct answer; 1 mark for a partially correct answer; 0 marks if the question part had been reached and considered by the student and was either incorrectly answered or not attempted. If the student appeared to have had insufficient time to attempt the question, evidenced by failure to attempt any subsequent questions, a blank was recorded instead of zero. (The distinction between a blank and zero was important for various calculations.) The scores for each component were then converted to scores out of 10.

Most of the 45 students who had made a serious attempt had run out of time and not completed all three discipline-specific components. Hence, the means and standard deviations for each of these disciplines were calculated using only the scores achieved by students who had attempted that particular discipline-specific component first, whereas scores for all 45 students were included in the statistics for the mathematics component (Table 12.1).

Table 12.1. Means and Standard Deviations for Scores on each Component

	Mathematics	Physics	Microbiology	Computer Science
mean	6.6	4.0	3.6	5.5
s. d.	2.3	2.9	2.8	2.8
N	45	13	16	16

Using the means and standard deviations given in Table 12.1, each student was assigned a ‘transfer rating’:

Transfer rating = z-score for first attempted component – z-score for mathematics

The formula compares the relative performance of a student in his or her first non-mathematical subject with performance in mathematics. Using this formula, a transfer rating of zero is assigned to a student who has performed at the mean in both mathematics and the other science discipline attempted. Such a student would be considered an average transferrer. A positive transfer rating indicates that the student has performed better (relative to the sample) in the scientific discipline attempted than in mathematics (relative to the sample). Such a student is considered to be a (relatively) good transferrer. The histogram of numbers of students in the sample with particular transfer ratings is bell-shaped, with the majority of students in the sample identified as average transferrers.

Unfortunately, there were some limitations in the use of the formula, particularly in the case of students who perform very poorly in both the mathematics component and the other discipline. The problem is obvious when the following example is considered. A score of zero in both mathematics and, say, the microbiology component would give a transfer rating of -1.29 - (-2.90) = +1.61, which is a very good transfer score relative to the sample. Yet it would obviously be wrong to describe this performance as indicative of good transfer abilities. In fact, it is simply not possible to test the transfer ability of a student when the marks scored in both components become too low, because any attempt to measure transfer ability presupposes that the student actually has some knowledge of mathematics to transfer in the first place!

Secondly, the formula will never assign a particularly high transfer rating to a student who performs extremely well on the mathematics component. For example, a student scoring 10 on both the mathematics component and the microbiology component may well be an excellent transferrer, but will be assigned a transfer rating of only 0.89. However, it is always difficult to effectively gauge the ability of someone who gets everything correct.

The graph of transfer rating against mathematics scores (Figure 12.3) highlights these problems. It shows a highly negative correlation between mathematics scores and transfer ratings ($r^2 = 0.301$, $p<0.01$).

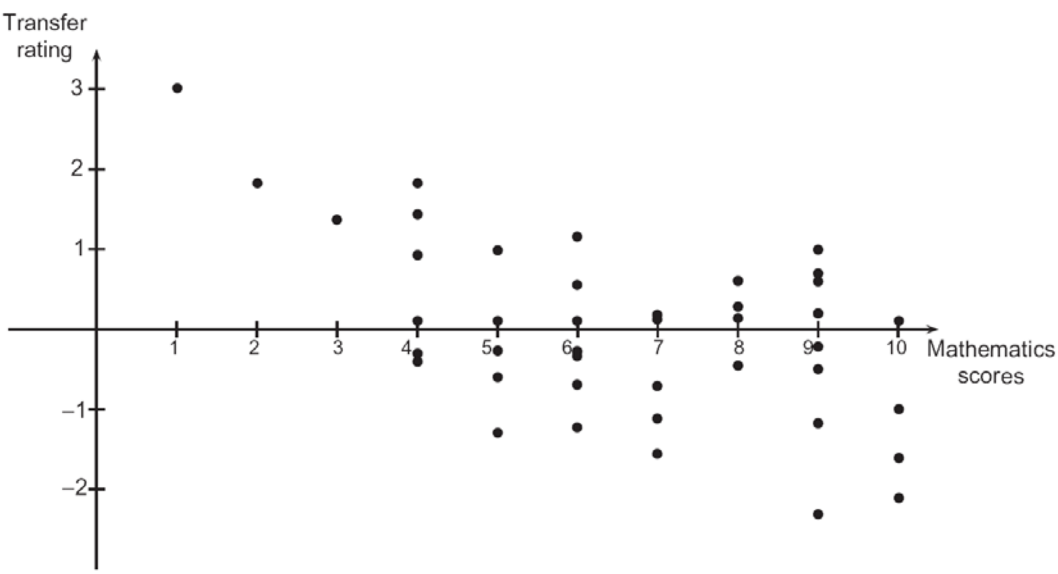

Figure 12.3. Transfer ratings vs. mathematics scores (note that 3 data points lie so close to other points as to be indistinguishable)

Assuming that the ability to transfer depends on the prior possession of some knowledge, it makes sense to consider the transfer ratings only for those students with a mathematics score close to the mean, or higher. If those students with a mathematics score lower than one standard deviation below the mean are disregarded, the remaining points on the graph (mathematics scores of 5 and above in figure 12.3) show no significant relationship between the mathematics scores and the transfer rating ($r^2 = 0.033$, not significant). This is satisfying, since the transfer rating is a measure relative to the mathematical ability of the student in question. However, in view of the major restrictions on the use of *transfer rating*, an alternative approach was developed building on the experience of the first experiment.

The second instrument

A new instrument was developed, consisting of a pure mathematics section (section A) that would be attempted first, with questions about logarithms and exponentials, and a discipline-specific second part (Section B), containing only a single multi-part microbiology question about bacterial concentration (Roberts, Sharma, Britton & New, 2007). It is significant that microbiology is not taught until second year at the University of Sydney, so no student was necessarily advantaged by being intimately familiar with the physical context chosen for Section B. The two sections of the test bear a similar relationship to one another as that between the mathematics and science sections in the first instrument.

Administering the test. First year science students at the University of Sydney volunteered to sit the test, in response to lecture visits and email requests. The test was administered to two separate groups of students, less than two weeks apart. Sample sizes were N=30 and N=19, respectively, for the two groups. The students gave permission for their university records to be accessed, yielding their first semester university results and high school results (if applicable). High school results included the Entry Ranking (UAI, standing for the University Admissions Index - a ranking out of 100 used for entry into universities in New South Wales) and marks for individual subjects. The university records also provided age and gender, which are considered important in any attempt to explain learning phenomena. It is important to note that the students who volunteered for participation in the study were self-selecting - they were not randomly selected and, as such, non-representative of first year science students. They were generally high-achieving students, as shown by the mean UAI of 94, and of the 49, only 7 were female.

Calculating transfer. Each question in Section A was matched to a question in Section B that required the use of the same mathematics, generating seven pairs of matched questions (Table 12.2).

Table 12.2. Matching of Section A questions to Section B

Section A	Matching part in Section B
1(a)	1
1(b)	2(d)(i)
1(c)	3
1(d)	-
1(e)	3
1(f)	-
2(a)	2(d)(ii); 3
2(b)	1; 2(d)(ii); 3
2(c)	2(d)(ii); 3

A student who gave the correct answer (score of 1) in corresponding question parts in both sections was awarded 2 marks for transfer for that part, while an incorrect answer (score of 0) in both sections resulted in a mark of zero (Table 12.3). If Section A was answered correctly but the corresponding question in Section B was incorrect, the mark was also zero, as this indicates that transfer has not occurred. Lastly, if Section A was answered incorrectly but Section B was correct, the student was awarded 1 mark. This reflects the view that transfer has occurred, but to a lesser degree than when answering correctly on both sections. There may be a subconscious process at work when answering Section A that prepares students for Section B, which provides an interesting question for further studies to address.

Only four out of seven parts in Section B are involved in the matching, and hence in the generation of the Transfer Index. This is a by-product of the natural setting of this project. The research team endeavoured to examine transfer in a real educational setting, rather than contriving a test with a one-to-one matching between all questions on both sections. There are difficulties associated with this approach, involving a trade-off between having a natural, non-contrived setting, and being able to use a greater proportion of the test answers in the calculation of the Transfer Index.

Table 12.3. Allocation of transfer score to matched questions

Section A score	1	0	1	0
Section B score	1	1	0	0
Transfer score	2	1	0	0

It should be noted that there is a distinct difference between the situations represented by the two right-most columns in Table 12.3. If a student displays knowledge in Section A and not in Section B, he or she has clearly not transferred that knowledge. Yet if a student scores zero in both sections, little can be adequately said about transfer - how can someone transfer something that he does not appear to possess? The Transfer Score does not attempt to discriminate between the two situations.

The overall *Transfer Index* given to a student was the normalised sum of the individual transfer scores on the seven pairs of mapped questions.

$$Transfer\,Index = \frac{\sum_{n=1}^{7} TransferScore}{14} \times 100$$

Correlations

Information on students' performances in selected high school and University subjects was compared with test results and Transfer Indices obtained using the Second Instrument, to see whether useful correlations could be found.

High school variables

The Entry Ranking (UAI) and marks for individual high school subjects were obtained for 36 students, all of whom had attempted at least one mathematics subject and at least one of physics, chemistry or biology. The average mark for the High School science subjects (*HSAvScience*) was calculated to provide an overall measure of a student's competence in science. High School physics (*HSPhysics*) was also considered separately as it is the science subject expected to be most sensitive to varying degrees of graphicacy. The mathematics that is regarded as a prerequisite for first year science at the University of Sydney can be taken at three levels but the lowest level was not considered in the analysis, since it was taken by very few of the cohort who did the test. This left Mathematics Extension 1 (*HSMathsE1*) and the more difficult Mathematics Extension 2 (*HSMathsE2*). The High School variables therefore were *UAI, HSPhysics, HSAvScience, HSMathsE1* and *HSMathsE2*.

Test variables

The variables specific to the test include *Section A* and *Section B*, which are the normalised marks from the two sections of the test. *Transfer* is the Transfer Index as described above while *Graph* refers to the normalised mark of a student on the graphing-related questions of Section B: Q.2(a), (b) & (d). The first two parts of these graphing questions require comprehension and graph reading skills, while part 2(d) requires comparison between graphs, interpretation and calculations, showing higher order cognitive thinking according to Bloom's taxonomy (Bloom, 1956).

University and generic variables

The University variables are averages of the first semester university marks in all mathematics (*UniMaths*) and science (*UniScience*) subjects. All but two of the students completed two mathematics subjects (mostly calculus and linear algebra courses), while all but six completed at least one subject in biology, chemistry, physics or earth sciences. The Generic variables were obtained from individual student records, with *Age* calculated to the nearest month at the time of the test. All of the variables are summarised in Table 12.4.

Table 12.4. Categorisation of project variables

High School	Test	University	Generic
UAI	Section A	UniMaths	Age
HSPhysics	Section B	UniScience	Gender
HSAvScience	Transfer		
HSMathsE1	Graph		
HSMathsE2			

Statistical correlations were performed in seeking to answer the following questions:

- Which, if any, of the Test variables best predict UniMaths and UniScience?
- Do any of the High School variables predict Transfer, or other Test variables?

A One-Sample Kolmogorov-Smirnov test (K-S test) showed that only one of the four Test variables (*Transfer*) was drawn from a normal population, so all correlations were performed using a non-parametric test, Spearman's rho (ρ_s).

Table 12.5. Correlation of Test Variables with University Variables

	Uni Maths	Uni Science		Uni Maths	Uni Science
Section A	ρ_s=0.56	ρ_s=0.59	Transfer	ρ_s=0.62	ρ_s=0.61
	N=47	N=43		N=47	N=43
	p<0.01	p<0.01		p<0.01	p<0.01
Section B	ρ_s=0.66	ρ_s=0.63	Graph	ρ_s=0.58	ρ_s=0.64
	N=47	N=43		N=47	N=43
	p<0.01	p<0.01		p<0.01	p<0.01

Table 12.6. Correlation of Test Variables with High School Variables

	UAI	HSAv Science	HSPhysics	HSMaths E1	HSMaths E2
Section A	ρ_s=0.45	ρ_s=0.44	ρ_s=0.48	ρ_s=0.56	ρ_s=0.61
	N=36	N=36	N=26	N=11	N=20
	p<0.01	p<0.01	p<0.05	n.s.	p<0.01
Section B	ρ_s=0.57	ρ_s=0.36	ρ_s=0.25	ρ_s=0.92	ρ_s=0.57
	N=36	N=36	N=26	N=11	N=20
	p<0.01	p<0.05	n.s.	p<0.01	p<0.01
Transfer	ρ_s=0.58	ρ_s=0.39	ρ_s=0.22	ρ_s=0.57	ρ_s=0.57
	N=36	N=36	N=26	N=11	N=20
	p<0.01	p<0.05	n.s.	n.s.	p<0.01
Graph	ρ_s=0.51	ρ_s=0.38	ρ_s=0.31	ρ_s=0.79	ρ_s=0.58
	N=36	N=36	N=26	N=11	N=20
	p<0.01	p<0.05	n.s.	p<0.01	p<0.01

(for Tables 5 and 6, n.s. = correlation not significant ; N = sample size)

Highly significant correlations were found between all University and Test variables, while the relationships between Test and High School variables are less uniform: some combinations show no correlation and others show very significant correlation (e.g., *HSMathsE1* with *Section B* or *Graph*). In addition to the associations between the Test and other project variables, a very interesting association was found between *Transfer* and *Graph* ($\rho_s = 0.72$, N = 49; $p < 0.01$). This was the strongest correlation besides the extremely high ones involving *HSMathsE1*, and it supports the findings of Gill (1999a) that ‘mathematical understanding related to the understanding of graphs and their slopes... may underly [sic] the ability to understand a number of higher order concepts’.

Models for predicting transfer

The chronological order of the variables in the project is High School → Test → University, while *Age* is measured at the time of the Test, and *Gender* is independent of time. This places a limit on the predictive powers of variables (e.g., *UniMaths* cannot predict *HSMathsE1*). Only models that included Test variables were considered, after eliminating all relationships without significant correlation (e.g., *HSMathsE1* with *Transfer,* Table 12.6). Ignoring the possible dependence of *Graph* on High School variables, two sets of regressions models were studied:

- those predicting *Transfer* from *Age*, *Gender* and the High School variables *UAI, HSAvScience*, and *HSMathsE2*
- those predicting University variables from *Age*, *Gender* and the Test variables *Transfer* and *Graph*.

In all of the models, *Age* and *Gender* were included, as these are often significant factors in education research.

Results of multiple regression. For each of the models, the relationships between the independent variables and the dependent variable were determined, and variables with a non-significant impact (based upon the significance of the standardised Beta coefficients, β) were progressively removed in a series of iterations, until the remaining variable(s) had satisfactory levels of significance.

Analysis of the first model resulted in exclusion of the variables *Gender*, *Age* and *HSAvScience* (*Gender* due to there being no females amongst the students selected by the model). The R^2 value for the resulting model (Figure 12.4) was 0.38 (N=20, $p<0.05$). *HSMathsE2* ($\beta = 0.50$, $p<0.05$) was a much more significant predictor of *Transfer* in this model than *UAI* ($\beta = 0.21$, $p<0.05$).

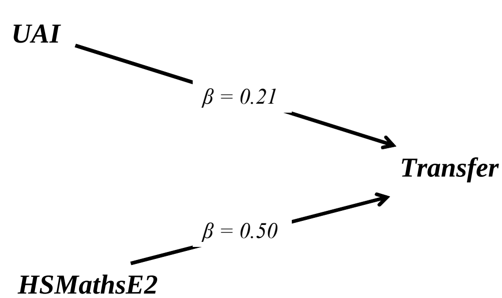

Figure 12.4. Final model for predicting *Transfer*

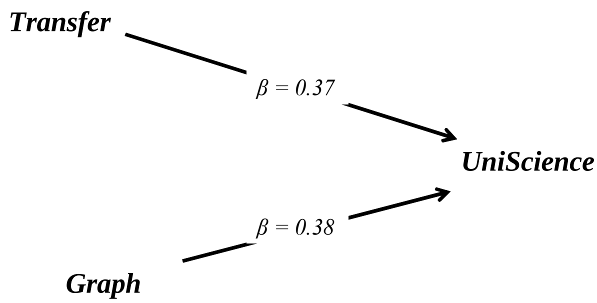

Figure 12.5. Final model for predicting *UniScience*

The second category of model moved from prediction of Test variables to using Test variables as the independent variables, with dependent University variables. For *UniMaths* as the dependent variable, the variables *Gender, Graph* and *Age* were excluded, leaving *Transfer* as the only significant independent variable ($R^2 = 0.38$, N=47, $p<0.01$). *Graph* and *Transfer* were the only independent variables with predictive value for *UniScience* ($R^2 = 0.48$, N=43, $p<0.01$) and standardised coefficients (β) of 0.38 ($p<0.05$) and 0.37 ($p<0.05$), respectively (Figure 12.5).

Our analyses show that, of the High School variables examined, only University Entry Ranking (*UAI*) and the marks for the most difficult mathematics subject (*HSMaths E2*) have any value in predicting mathematics transfer ability, with *HSMaths E2* being the most reliable predictor. Based on the Second Instrument, the results of the questions relating to graphicacy as well as the calculated Transfer Index were both useful in predicting university science results.

Application of the research to improving teaching and learning

To date most of our emphasis has been on development of tests to measure transfer and meaningful ways to analyse the data generated. It has been seen that the ability to transfer mathematics is a good predictor of performance in first year University mathematics and science, and is itself correlated with the Entry Ranking and the mark in high school Mathematics Extension 2. At this time it is not known to what extent the ability to transfer mathematics can be increased by training, or if a low level of numeracy in scientific disciplines due to poor transfer ability can be augmented by remedial teaching in a few key areas of mathematics.

So while there have been few conclusions that would suggest changes in teaching practice to improve transfer, work on the project has taught us two important lessons that have clear implications for teaching and learning. Firstly, communication between mathematicians and academics in other scientific disciplines is essential. We discovered that our use of mathematics is often different, in ways which are unlikely to be helpful to students. The second lesson arises from the difficulties that we all encountered in understanding questions written by our colleagues, set in the context of disciplines other than our own. We must take extreme care in our teaching to ensure that we do not assume more knowledge on the part of students than they possess.

One interesting finding has been that transfer ability is positively correlated with graphicacy, although we do not know whether superior ability to interpret graphical representations of mathematical data is a cause or consequence of superior ability to transfer mathematical learning. However the strength of the correlation has encouraged some of us to change our emphases in teaching. We now devote more time to explaining the interpretation of graphs in the context of our own scientific disciplines. Further work is needed to confirm that this approach improves mathematics transfer and numeracy.

So far our investigations have only analysed data concerning transfer of mathematics knowledge and skills related to one area, that of exponentials and logarithms, but they could be applied to other mathematics contexts and to other cohorts of students. In so doing, our approaches will allow identification of other useful questions, the answers to which will inform our teaching practices and build a community of practice across the various disciplines that rely on mathematics transfer.

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