ASSESSMENT OF A-PRIORI AND DYNAMIC EXTENDED LEARNER PROFILING FOR ACCOMMODATIVE LEARNING

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Abstract

Undergraduates often have experiences during their period of study that can have adverse effects on their ability to complete a particular course. This paper describes the use of an online questionnaire to integrate an exploration of learning styles, as presented by Felder and Silverman in 1988, with an investigation of additional student risk factors. The report demonstrates the complexity of marking and evaluating the validity of such studies, be they online, or in paper formats. It also investigates a method of evaluating the data before committing the evaluation technique to software. The learning styles utilised are; Visual/Verbal/Kinaesthetic and Global/Sequential. The information gathered about learning styles can inform and stimulate tutor reflection on suitable teaching styles. The risk factors considered include; academic expectations, subject interest, ability to understand, examination nervousness, mathematical ability and age. The ability to define referred learning styles and learner risk factors results in the creation of individual Learner Profile. Information stored on an online database as the questionnaire responses are uploaded. It also gives an overall impression of the learning styles and the risk factors of the individual and of the cohort. Risk factors can also be considered as support requirement indicators. The investigation reported in this paper forms part of a continuing philosophy of student support which has been successfully employed within the School of Engineering Science and Design at Glasgow Caledonian University for some time. This process of support, known as the 'Triple C' model (standing for care, control and consistency) has dramatically increased the retention and progression of first year undergraduates to second year over the last three academic years.

The methodology begins during induction when undergraduates are asked to complete an on-line 'Learning Styles' questionnaire comprising 44 questions. They receive immediate feedback on their own learner profile, including current learning style, in the form of a report which they can print or save. Examples of the types of feedback provided are presented in the paper, indicating how the learner can have more than one learning style, how those learning styles may overlap and how they may overcome potential difficulties. The paper further reports on the collated results of the questionnaire for the

cohort and describes how those results are used by the First Year Tutor when allocating Personal Tutor groups to academic staff. Students at ‘higher risk’ are put into smaller tutor groups and are allocated personal tutors who have more experience in dealing with particular categories of support needs.

In addition to the presentation of data, the relationship between risk factors and class absence is analysed. The absence data was gathered using an absence management software tool called KELPIE (Keeping Every Lecturer Properly Informed Electronically). Although it is not the primary purpose of the paper to discuss the success of the ‘Triple C’ model, a brief description of how KELPIE and the philosophy works is provided to contextualise the learner support environment. This work will be taken further to provide an analysis of relationships between risk factors, absence data and student performance when student performance results are made available.

Finally, the paper outlines how the School continues to develop learner and cohort profiling, describing a framework where the profile of an individual will be used to determine appropriate learning environments as the learner develops or as their risk factors change. The framework aims to develop a learner profile for each individual where learning styles, entry risk factors, evolving risk factors, performance levels and special needs are considered with the intention of delivering Learning Objects and Learning Support best suited to each individual. This requires the further development of Intelligent Agents within software tools to accommodate individual learning profiles.

Background

This work is an extension of work carried out by Abdul R. Adhami for his final year project during completion of his BEng Honours Degree in Electrical and Electronic Engineering. The work presented draws significant content from Abdul’s project report [1].

Investigations carried out over the past 3 years at Glasgow Caledonian’s Intelligent Technology Research Centre (ITRC) have focussed on individuals experiences that contribute to the successful or unsuccessful completion for the first year of study. In general students must overcome potential barriers of a personal, academic or circumstantial nature at some point in their academic career of varying degrees of severity, in order to give themselves the best chance to succeed. The development of the student support philosophy to allow direct intervention at critical stages in the students development when necessary has extended beyond that already available in most educational institutions by incorporating a “someone really cares” attitude. Students running the risk of failure or incompletion may not be able to identify the potential hazards that they are exposed to and therefore may not see a way forward. Traditionally, students experiencing difficulty would have to contact Student Services for advice if they felt that they were having problems, however, the nature of the problem itself may be such that they cannot see this as a helpful route or as in some cases students may not know of the existence of such support.

In addition to external influences or personal circumstances, the student may have personal attributes that could inhibit or enhance their ability to learn particular topics. The chosen method of delivery of a particular topic may not suit the learning preference of all students in a cohort; therefore it would seem reasonable to assume that if different modes of delivery were available, students could select material that best suited their needs or as is anticipated suitable materials can be provided depending on the learner's preference. In order to do this effectively, students must at the outset, understand what works best for them and how to take advantage of their own preference.

In this study no expertise is claimed in learning style theories, or on their reliability and validity; a topic studied in detail by Coffield et al [2] where 13 of 71 learning styles are critically reviewed. The review comments, '*now that most instruments can be administered, completed and scored online, it has become a relatively simple matter to give ones favourite learning style inventory (no matter how invalid or unreliable) to a few hundred students as part of their course; in this way, some trivial hypothesis can be quickly confirmed or refuted'* [2]. However, we feel that valuable information can be derived about an individuals learner profile by their delivery when used as a vehicle for determining additional risk factors. In addition the use of the learning styles questionnaire and provision of feedback is considered an inclusive exercise during the students' induction, when it is considered that at this stage the seeds of student-tutor relationships germinate. The learner profiles developed are based on some but not all of the classifications described in the Felder-Silverman Learning Style Model [3]. This study sets out to classify the students' sensory dimensions as Visual, Verbal or Kinaesthetic, or some combination of the above and as Global/Sequential Learners in order to assist in the provision of learning materials to suit or if appropriate, compliment their preference. In addition, the questions are specifically set to determine a level of tutor support.

Learner Profile Categories

The online questionnaire consists of 44 questions spanning the 11 categories listed in Table 1 below. Categories 1 – 9 are explored using simple 'strongly disagree, disagree, unsure, agree and strongly agree' responses, category 10 requiring 'yes/no' responses whilst the last category offers a choice from a range of values. Each response is allocated a score to be used in determining the students learning preference (style) and a potential risk indicator. A number of questions address each category, and are posed randomly to the students in blocks of 8 questions per page. The learning style categories form the basis of a report generated on completion of the questionnaire. The report allows the student to receive immediate feedback and advice on their performance and learner profile.

Table 1

	Category Title
1	Academic Expectations
2	Subject Interest
3	Understanding Ability
4	Exam Nervousness
5	Mathematical Ability
6	Visual Learning Dimension
7	Verbal Learning Dimension
8	Kinaesthetic Learning Dimension
9	Global / Sequential Dimension
10	Academic Risk
11	Personal Risk

Learning Style Categories

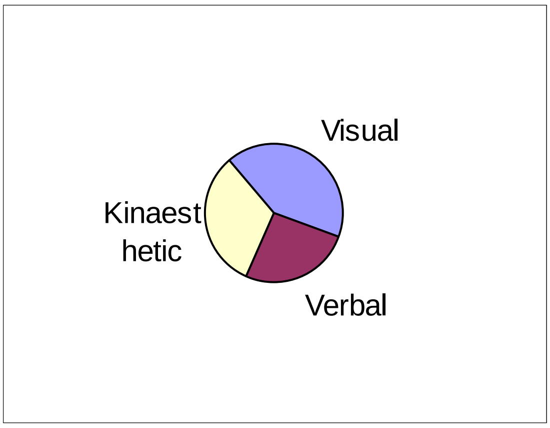
Categories 6-9 address the students learning style preference and comprise of the questions listed in Table 2.

Table 2

Category	Question
Visual Learning Dimension	I feel the best way to remember something is to picture it in my head
	I typically follow written instructions better than oral ones
	I learn better by reading than by listening to someone
	I like teachers and lecturers who put a lot of diagrams on the board rather than spend a lot of time explaining
Verbal Learning Dimension	I would often rather listen to a lecture than read the material in a textbook
	I frequently require explanations of diagrams, graphs, or maps
	I often prefer to listen to the radio than read a newspaper
	I frequently sing, hum, talk or whistle to myself
	I enjoy participating in discussions and class debates
Kinaesthetic Learning Dimension	I am constantly fidgeting (e.g. tapping pen, playing with keys in my pocket)
	I am excellent at finding my way around even in unfamiliar surroundings
	I need to actively participate in an activity to learn how to do it
Global / Sequential Dimension	I am more likely to start working on a solution immediately rather than trying to fully understand the problem first
	When writing a report, I am more likely to work on the beginning and progress forward, rather than work on different parts and then put them in order

These questions are used to determine learning preference and are the basis of the report that forms the 'inclusive' element during induction week. Students may find that they have a strong tendency for one particular dimension, however the nature of the scoring mechanism allows for a description to indicate more than one preference. The feedback provided is selected depending on a score formed by the choice (agree / disagree range) where the highest score for all categories indicates the principal learning style. The other category scores are examined, and, if found to be within 5% of the highest category score, that category is considered as part of the learning profile mix. An example of the report is provided in Appendix A, and offers students the opportunity for reflection, providing advice on how to enhance their learning abilities. It indicates their learning preference or mix together with information on sequential/global tendencies that also is based on a range of possibilities from principally global to principally sequential. Included in the report are comments relating to risk categories 1 – 5, explaining possible pitfalls that may be encountered and how to avoid them.

Figures 1 and 2 indicate the principal learning preference and global/ sequential tendency for students taking the questionnaire in 2004. The questionnaire was completed by 172 students and includes engineering, science, and design cohorts.



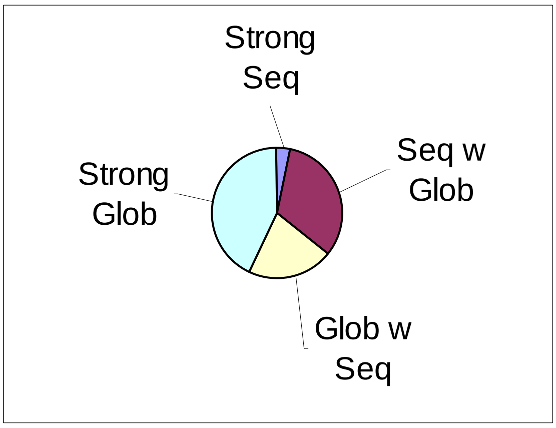


Figure 1. Principle Learning Preference **Figure 2. Global/Sequential Mix**

A pilot questionnaire was presented to first year BEng Electrical and Electronic Engineering students in 2003. Those students were asked to comment on the questionnaire and the report. Feedback from students included the comments below:

- “I like to be analysed. It is interesting and some of it hits home”.
- “The questions: Do you talk to yourself? Do you hum or sing to yourself? I found these amusing as I do both”.
- “The end report was quite accurate”.
- “Overall really good test as I feel it gave feedback that related to me”.
- “I liked the way it gave a description of me at the end”.

These comments from students are exactly what the inclusive element of induction week intends to accomplish – by providing students with an experience that encourages thought and allows reflection, the students hopefully find learning in the School an enjoyable process. Early enjoyable experiences are of primary importance in the philosophy.

Risk Indicator Categories

Categories 1 – 5 and 10 and 11 form the potential risk indicators. The questions are presented to investigate additional external/personal influences that may inhibit retention and successful completion of year 1. The study is carried out with a view to determining an overall risk estimation that may be used by the first year tutor in allocating personal tutor groups. In addition, research in this area will continue with the intention to investigate correlation will absence data derived whilst implementing the Triple C model [4]. The questions are grouped 1-5 and 10-11. Categories 1–5 are answered using the same agree/disagree format for learning preference. Category 10 requires the simple yes/no response and category 11 responses ask for a response falling within a range of values. Each of the categories have, at this stage been given equal consideration by applying a weighting factor 1 to each, because they are all assumed to be potentially significant. Tables 3 and 4 show the categories and the associated questions with possible response types.

Table 3

Categories 10 and 11	**Question**	**Response**
Academic Risk (AR)	Have you started, but not completed, a University or College course before?	Yes / No
	Have you left your parents' home for the first time to start University?	"
	Was the course you are about to study your first choice?	"
	Did you apply for the course through the UCAS Clearing System?	"
	Are you the first person in your immediate family (i.e. grandparents, parents, brothers and sisters) to begin a University course?	"
Personal Risk (PR)	What age are you?	17, 18 -19, 2 - 22, 23+
	If you have a part-time job you will keep while you are at University, how many hours a week on average do you expect to work?	Don't work, 1 – 8 hrs, 9 – 20 hrs, More than 20 hrs
	How many other students do you already know who will start the course at the same time as you?	0, 1, 2, 3 or more

Table 4 Potential Risk Indicators

Categories 1- 5	Question	Response
Academic Expectations (A)	I expect to get excellent marks in my exams	Agree/Disagree
	I am confident that I will learn even the most difficult theoretical subjects that I study	"
	I only want to study enough to get me a pass mark in my exam	"
	It is important for me to do well in my studies and show others (my family, friends, colleagues) what I am capable of	"
Subject Interest (I)	I am only interested in mastering learning tasks that are required in real working life	"
	I prefer to study theoretical subjects that interest me, even if I find them difficult	"
	When I am very interested in a subject I am also interested discovering new information related to it	"
	I find it most rewarding when I can research a subject as thoroughly as possible	"
	It is essential for me to understand the topics contained in my subject	"
Understanding Ability (U)	I often feel so lazy and bored with reading that I discontinue studying	"
	When reading, I try to combine information from various sources (such as notes, textbooks, discussions etc)	"
	I often give in when studying difficult subjects by concentrating on easier aspects of them	"
	I have no difficulty in following things through even if I find them uninteresting	"
	I try to deal with things by myself without help from others	"
Exam Nervousness (EN)	Nervousness during exams affects my performance	"
	When taking part in practical assessments, I am more concerned about failing and what will happen as a result	"
Mathematical Ability (M)	I generally have little difficulty in understanding and working with numerical problems and applying equations	"
	Given the choice in an exam, I usually favour mathematical/equation type questions over general explanation and descriptive ones	"

Investigation of Potential Risk Indicator scores identify some very interesting results as shown in Figure 3, where it can be seen that 70% of students (121) enrolling on a course in the School would have preferred a different course. 46% were the first person in their immediate family (siblings, parents, grandparents) to attend a University or College.

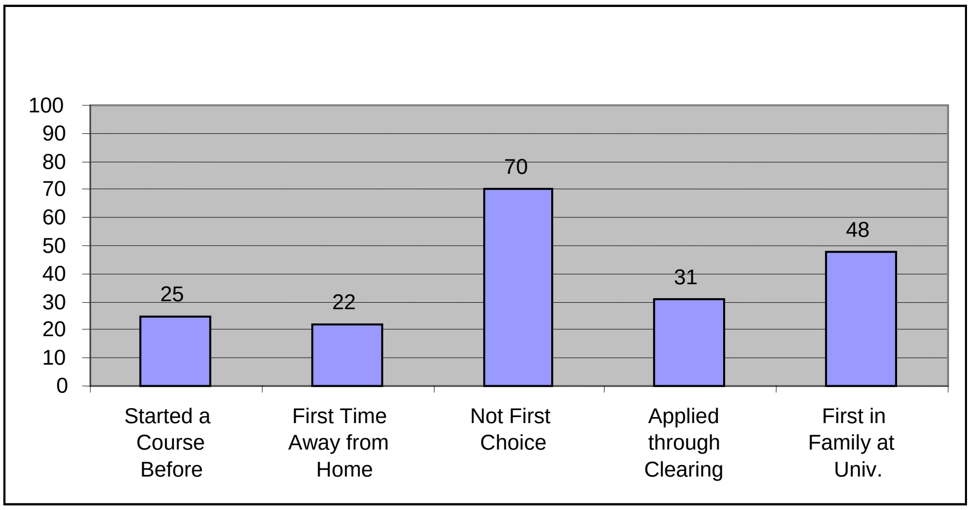


Figure 3. Academic Risk Indicators

The results of the questionnaire are available to the First Year Tutor at the end of induction week. Higher risk students are put into smaller personal groups and are assigned to academic staff that have the expertise to provide appropriate levels of support. Some direct profiling of students and staff also takes place using the detailed information. An example of this is the tutor group that is formed from older students whose personal tutor himself came into education later in life. It is believed that this personal tutor has an empathy with mature students who also benefit from the co-mentoring of being part of a mature group.

Absence Data and Monitoring

The absence management was undertaken manually in previous years by centralised collation of absence information which resulted in the categorisation of students into a pastel traffic light system of green for excellent attendance, yellow for good attendance and pink for poor attendance. Students were sent letters on the colour of paper that reflected their category of attendance and ‘pink students’ were interviewed.

The system of absence management has been made more efficient by the development of an in-house suite of software tools called KELPIE. KELPIE is an online system which allows absence data and other information about students, including any information available about their special needs, to be displayed online for academic staff. It also generates coloured absence letters to first year students and coloured absence emails to second and third year students. It is believed that although absence itself can be a problem, it is frequently also the manifestation of greater problems.

Risk Analysis from the Questionnaire

The major goal of the study is to analyse the data with a view to determining how to indicate the likelihood of failure or success. This may be possible by investigating input variables and applying weighting factors to each with the intention of providing a level of risk that can be quantified and then tagged as high, moderate or low. If this were possible, the risk tags could be applied to students very close to time of entry and used for automatic allocation of Personal Tutor groups. When a response is considered a positive contribution to risk, the risk indicator is assigned a value 1 for that response, where no risk is considered, a value 0 is applied. This results in an evaluation that is simply based on a true/false risk contribution per question. The complex nature of the problem will require a solution that not only takes the risk contribution into account, but also includes its significance. The concept of Artificial Neural Networks may prove useful for this purpose.

A data analysis was carried out using MS Excel to investigate apparent correlation coefficients for all categories listed in Tables 3 and 4 with additional absence data collated using KELPIE for semester A. A table indicating all results of the correlation exercise is presented in Appendix B.

Of particular interest are areas where apparent correlation exists between risk indicators and absence for Semesters A and B since it has already been suggested [4] that progression into second year depends a great deal on attendance.

For the purpose of this study, and at this moment, we consider positive correlation to exist where the correlation coefficient is greater than 0.14 and negative correlation exists when less than -0.14. Although small values, they do show the most promising possibilities when absence is the focus as was initially thought. Table 5 shows the risk indicators and their corresponding correlation coefficient with Semester A and B absence.

Table 5

	Semester A	**Semester B**
Subject Interest		-0.20
Mathematical Ability	0.15	0.25
Started a Course Before	0.18	
Course was not First Choice	-0.15	-0.19
Applied through UCAS Clearing	0.15	0.22
First in Family at University	-0.22	
Age under 17 yrs	0.15	0.22
Semester A Absence		0.64

It would seem that at this stage, some relationship may exist with data collated from the questionnaire where students had some combination of the following profile:

- A Low subject interest
- Low mathematical abilities
- Had started a different course before
- Were not on their preferred course
- Were under 18 years of age

Weighting Factors

It may be possible to use techniques applied in Neural Network (NN) theory to determine appropriate weighting factors for the risk indicators to evaluate the significance of the risk contribution. Neural Networks are based on the biological neurons that exist in the brain. The brain consists of highly interconnected cells called neurons and it is generally understood that thought processes and pattern recognition are functions of the neurons and connections between them. The neuron has three principle components; the dendrites, the cell body and the axon as shown in Figure 4.

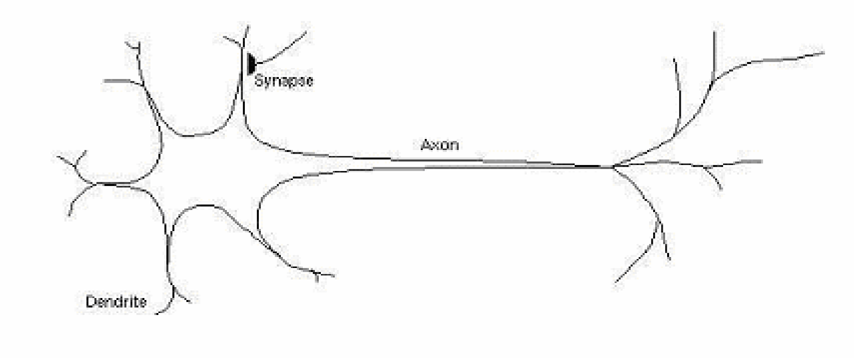


Figure 4. The Biological Neuron [5]

The dendrites are the receptors (an input to the cell body), the cell body effectively sums and thresholds the incoming signals providing an output on the axon if the sum and thresholds meets specific criteria. The axon is connected to other neurons via the point of contact, the synapse, providing subsequent inputs on other dendrites and cells.

A very simple artificial neuron is indicated in Figure 5 where there is only a single input. The input (p) is multiplied by a weighting factor (w) to form (w*p), the input to a summing function, where it is added to a bias (b). The summer output (n) is fed to a transfer function (or activation function, (f), which produces the neuron output (a). When this model is compared with the biological neuron, the weight (w) corresponds to the strength of the synapse, the summing and transfer functions represent the cell body, and the output (a) represents the signal on the axon [6, 7].

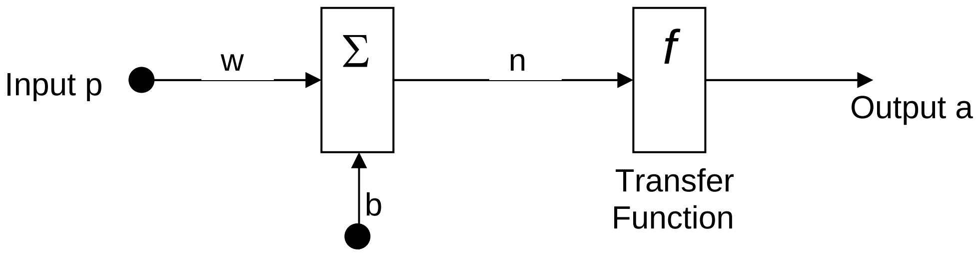


Figure 5. The Artificial Neuron

A simple artificial neuron can be modelled mathematically as:

$$a = f(wp + b)$$

The output depends upon the particular transfer function chosen, the bias is similar to the weight, both being adjustable and the output depends that weighted input with a transfer function. The transfer function in artificial neurons is chosen depending on the desired output and may be classified as Hard Limit, Linear or Log-Sigmoid [6]. To determine the weighting factors for each input, the neural network must learn how to provide best effort approximation of an output status or level, by training.

The model above is the very simple single input-single output artificial neuron. A significant increase in NN complexity arises when the analysis required consists of multiple inputs and outputs.

Student Performance

The discussion so far only has only addressed the possibilities of correlation between risk indicators and absence data. Of more interest is the correlation between the risk indicators, absence data and the student performance. At time of writing, first year results are not available, therefore the results of this analysis will be made available at a later date.

Future Work

The evaluation of the questionnaire is complete to the extent that it can be used to determine entry risk indicators suitable for use by the First Year Tutor for allocation of personal tutor groups. A method must be identified to investigate the apparent correlation between the data sets and the most significant risk indicators and weighting factors to be used to do this automatically. It is anticipated that the application of neural network modelling may prove vital in determining weighting factors to match suitable inputs from the student data to appropriate outputs.

KELPIE will evolve to become a comprehensive dynamic profiling tool that will enable entry and evolving risk factors to be compared with absence data to allow a more focussed approach to student monitoring. The profiling, with appropriate dynamic learning preference data will be harvested by intelligent agent applications, and may be processed using weighting factors and transfer functions approximated using neural network theory to allow the ability for highlighting student risk at any stage in their academic career and also allow identification of students most at risk automatically, at time of entry.

KELPIE may also develop to deliver learning objects to students suited to particular learning preferences based on similar techniques providing dynamic accommodative learning. It is with this in mind that research also focuses on the generation and use of learning objects. ITRC contributes to this area of research as co-ordinators of the ReSET consortium funded by JISC, where we are currently developing and packaging legacy material suitable for populating the JORUM repository.

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Appendix A

Your Report

You have the determination to succeed and expect good results in your choice of programme and in your exams. The more confidence you have in your self the more likely you will be to succeed. Your hard work will translate into marks and this is a very good start.

You also have relatively high interest in your choice of programme and are willing to try hard to obtain success. Your interest should help in adding some enjoyment to your learning at University. Having high interest and motivation in subjects makes you more likely to succeed.

In terms of your understanding ability you should have little problem in passing. The more you make an effort to learn and understand then the more likely you are to progress! Never give up, if you can’t understand something always ask for help, never leave things until the last minute.

You indicate that you have had no previous problem with nervousness in exam situations. Exam nerves or stress are very common among university students. It can be very distressing and sometimes debilitating. Often students find they get good coursework marks but come exam time their marks drop. This could be because of either poor exam preparation techniques and/or stress and nervousness levels becoming too high. Hopefully you will continue not to have this problem but if you do, you can get help from the Effective Learning Service in the library.

Based on your answers to this questionnaire, you generally seem to have little difficulty in dealing with numerical and mathematical problems. There is nothing that is designed to be tricky or beyond your own ability in this programme. The University offers lots of extra help with mathematics.

LEARNING STYLE As for your learning style Elaine, You may learn better from hearing words spoken and from oral explanations. You may remember information by reading aloud or moving your lips as you read, especially when you are learning new material. You could benefit from hearing audio tapes, lectures, and class discussions. You may therefore benefit from recording lectures or recording your own revision notes and then listening to them. It appears that you are an auditory style learner.

LEARNING APPROACH In terms of a learning approach there are both sequential and global learners. Sequential learners tend to gain understanding in linear steps, with each step following logically from the previous one. Global learners tend to learn in large jumps, absorbing material almost randomly without seeing connections, and then suddenly "getting it." Sequential learners tend to follow logical stepwise paths in finding solutions; global learners may be able to solve complex problems quickly or put things together in novel ways once they have grasped the big picture, but they may have difficulty explaining how they did it. I feel that you are more of a sequential learner. Being one or the other is not better but it should inform you how you tackle your studying. Most university courses are taught in a sequential manner but you can fill in any gaps yourself by consulting references. When you are studying, take the time to outline the lecture material for yourself in a logical order. In the long run doing so will save you time. You might also try to strengthen your global thinking skills by relating each new topic you study to things you already know. The more you can do so, the deeper your understanding of the topic is likely to be.

Appendix B

	Academic Expectations	Subject Interest	Understandin g Ability	Exam Nervousness	Mathematical Ability	Visual Learner	Verbal Learner	Kinaesthetic Learner	Sequential / Global	Started a Course Before	First Time Away from Home	Course was not First Choice	*Applied through UCAS*	First in Family at University	Aged 17 yrs	Work Commitment	Semester A Absence	Semester B Absence
Academic Expectations	1.00																	
Subject Interest	0.22	1.00																
Understanding Ability	0.29	0.19	1.00															
Exam Nervousness	-0.11	0.15	-0.04	1.00														
Mathematical Ability	0.04	-0.07	-0.03	0.00	1.00													
Visual Learner	0.04	0.00	-0.07	0.04	-0.10	1.00												
Verbal Learner	-0.04	-0.12	-0.28	0.07	0.03	-0.19	1.00											
Kinaesthetic Learner	-0.11	0.03	-0.25	0.19	0.04	-0.08	0.21	1.00										
Sequential / Global	-0.06	-0.10	-0.26	0.01	0.09	0.06	0.32	0.09	1.00									
Started a Course Before	-0.02	-0.14	-0.05	-0.08	0.02	-0.13	-0.05	0.20	-0.07	1.00								
First Time Away from Home	0.07	-0.11	-0.14	-0.17	0.03	-0.01	-0.03	-0.04	0.17	0.06	1.00							
Course was not First Choice	0.01	-0.08	0.18	-0.18	-0.11	-0.04	-0.13	-0.16	-0.14	-0.07	-0.02	1.00						
Applied through UCAS Clearing	-0.03	0.03	-0.02	0.06	0.01	-0.07	0.06	-0.02	-0.05	-0.01	-0.11	-0.05	1.00					
First in Family at University	0.00	-0.03	0.09	0.05	-0.04	-0.07	-0.05	0.02	0.02	0.01	-0.01	0.17	0.04	1.00				
Aged 17 yrs	-0.03	0.03	-0.02	0.06	0.01	-0.07	0.06	-0.02	-0.05	-0.01	-0.11	-0.05	1.00	0.04	1.00			
Work Commitment	0.00	0.00	-0.05	0.04	-0.01	0.01	0.18	0.19	0.11	0.09	-0.33	-0.11	0.03	0.06	0.03	1.00		
Semester A Absence	0.01	-0.04	-0.13	0.00	0.15	-0.01	0.05	0.12	0.12	0.18	0.03	-0.15	0.15	-0.22	0.15	0.10	1.00	
Semester B Absence	-0.02	-0.20	-0.06	0.02	0.25	-0.11	0.05	0.03	0.13	0.02	0.14	-0.19	0.22	0.03	0.22	-0.04	0.64	1.00