Learning Styles a Potential Predictor of Student Achievement in Remote and Virtual Laboratory Classes

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***Abstract**: Remote and virtual laboratories are becoming increasingly prevalent as ways of providing engineering students with the laboratory learning experience. Previous literature suggests that there may be differences in the nature of these learning experiences, leading to difference in the learning outcomes achieved by students exposed to these different access modes.*

This paper investigates the impact of the students' preferred learning styles upon these changes in learning outcomes. This study shows that for some learning outcomes, the differences are not dependent solely upon access mode, but rather upon the interaction of access mode and learning style. Some styles are more susceptible to mode-based variations, whilst others show little change between the modes. This suggests that the students' preferred learning styles may be a potential diagnostic tool for determining which access mode will most enhance a given student's learning opportunities.

Introduction

Laboratory classes are widely accepted as a crucial part of an undergraduate engineering degree. Good pedagogical reasons, such as illustrating and validating analytical concepts, introducing students to professional practice and to the uncertainties involved in non-ideal situations, developing skills with instrumentation, and developing social and teamwork skills in a technical environment (Scanlon et al. 2002), (Antsaklis et al. 1999), illustrate the need for their inclusions in undergraduate curricula.

The traditional undergraduate lab class is comprised of a small group of students and a demonstrator, grouped around a piece of hardware located in a laboratory. The students conduct a series of experimental procedures as outlined in the laboratory handout; they record the data from the hardware; and they write up a report based on these data and the underlying theory in the week or two subsequent to the session.

This traditional, proximal model is coming under increasing pressure because of the changing demands of engineering courses. Scheduling increasingly large numbers of small groups of students, each of which requires an hour (or more) of continuous and adequately supervised access to an expensive piece of laboratory equipment, is a difficult and expensive task. An increasingly prevalent solution to this dilemma is the use of alternative access modes – either simulation (or virtual) laboratories or remote access to real laboratory hardware. Web-based remote labs have been offered by universities in undergraduate engineering courses since 1996 (Aktan et al. 1996), with the number and sophistication of these efforts growing each year (Trevelyan 2003; Ma and Nickerson 2006).

The initial motivations for the field were logistical; however more recently the educational impact is being more seriously considered. Coarse-grained analysis of overall scores found no differences between the remote and proximal modes of access to a jet thrust laboratory (Ogot et al. 2003). A finer grained analysis of an accelerometer calibration laboratory has shown that whilst overall marks may be similar, there are significant differences between modes for some learning outcomes (Lindsay and Good 2005), and also differences in the way in which students perceive their laboratory experience (Lindsay and Good 2004).

There is presently no consensus as to whether one mode of access is superior to the others; indeed each mode has its proponents and its detractors (Ma and Nickerson 2006). Much of the contention arises from an inability to directly compare different access modes, with different laboratory objectives and evaluation methods reported in different studies.

Having different objectives for the different modes is more than just a confounding factor for comparison – it is in fact the greatest potential pedagogical advantage of the different access modes. Simulations allow for students to adopt a mastery learning approach, taking as much time as they wish without increasing the cost to the department. Remote laboratories relax the constraints imposed by scheduling. Each mode is able to achieve distinctly different outcomes – but to be able to fully realise this potential, it is important to understand which outcomes are supported by which modes, and which other factors can affect these outcomes.

Differences in learning outcomes are suggested by a constructivist analysis of the remote and virtual laboratory paradigm (Lindsay et al. 2007). Both modes require a separation (both physical and psychological) between the learners and the equipment. Both modes require a technology-mediated interface to close this difference. Either of these constructs can affect the students' laboratory experience; the combination of the two can significant impact the way the students construct their learning.

What has not been explored in the context of remote and virtual laboratories is the way in which the students' preferences for learning styles interact with these alternative access modes. The different modes offer a different learning environment to the students – an environment that may not be suited to their learning styles.

This paper reports on the re-analysis of previously reported data (Lindsay and Good 2005) to incorporate the students' preferred learning styles as independent variables. This analysis shows clear indications that the students are not an inert part of the variation of learning outcome – rather, the students' preferred learning styles can have a significant impact upon the extent to which they achieve some of the learning outcomes.

The laboratory class

The laboratory which was investigated in this instance was the calibration of a piezoelectric accelerometer. This class forms a practical component for a third-year Mechanical Engineering unit in Data Acquisition and Control. In this laboratory experiment, the accelerometer is mounted on an electrodynamic shaker, which is excited using signals generated by a spectrum analyzer. The velocity of the accelerometer is also measured by a laser Doppler vibrometer. This velocity signal, and the accelerometer's own acceleration measurement, are analyzed using the spectrum analyzer. The hardware is shown in Figure 1 and Figure 2.

Figure 1: The laboratory hardware

Figure 2: The accelerometer mounted on the electrodynamic shaker

This laboratory is conducted primarily through a single point of control, the spectrum analyser (Figure 3). As a result, the alternative access modes are simply a matter of providing a remote mechanism for controlling the spectrum analyzer, achieved in the remote implementation using a General Purpose Interface Bus (GPIB) connection.

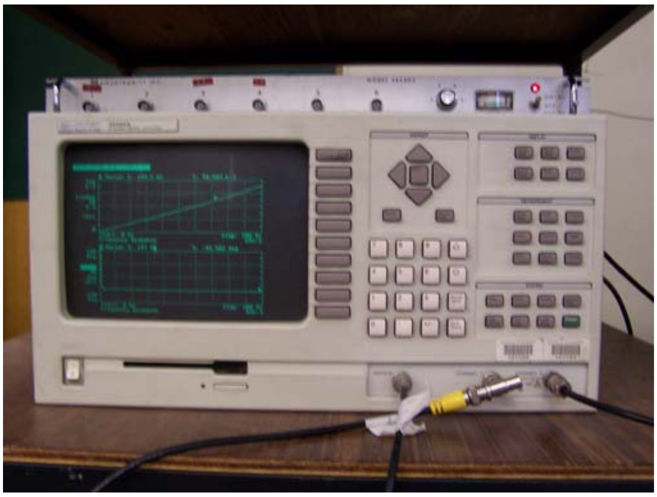

Figure 3: Real Analyzer Interface

A MATLAB Graphical User Interface (GUI) (shown in Figure 4) was constructed to represent the spectrum analyzer and to provide the user with access to the functionality of the spectrum analyzer that was necessary to perform this experiment.

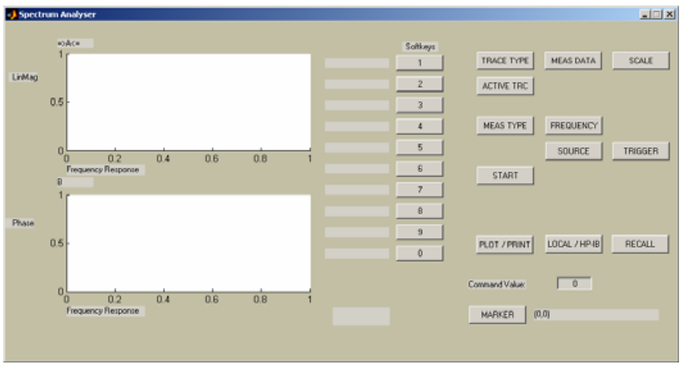

Figure 4: GUI Interface

A simulation of the system was also constructed, using the same GUI as the remote interface. This simulation used recorded data from the system to generate responses interactively for the user. The simulation access mode differed from the remote mode only in the students' belief of whether there was actually real hardware involved. All other factors were kept the same. In this way some insight into the importance of the students' awareness of the access mode could be gained.

The cohort for this laboratory class comprised 146 third-year students drawn from a number of degree programs, including Mechanical, Mechatronic, and Environmental Engineering. The students had all completed a prerequisite course in linear feedback control (almost all in the semester prior to this course).

All students were marked according to an 11-criterion marking rubric. Linear combinations of these criteria are used to determine values for eight learning outcomes. It is these learning outcomes that are used as the comparison metrics. The data from the overall cohort has previously been analysed to determine the impact of mode upon these learning outcomes, and significant differences were found and reported (Lindsay and Good 2005). This paper extends this analysis to consider the interaction between the alternative access modes and the students' learning styles.

The Evaluation Tools

The students each submitted a written report on their laboratory class, due two weeks after the completion of the laboratory. The reports were marked according to whether specific behaviors were represented. From these behaviors, eleven criteria marks were determined; and from these eleven criteria marks, measures of eight learning outcomes were constructed. The interaction among the behaviors, criteria, and outcomes is illustrated in Figure 5.

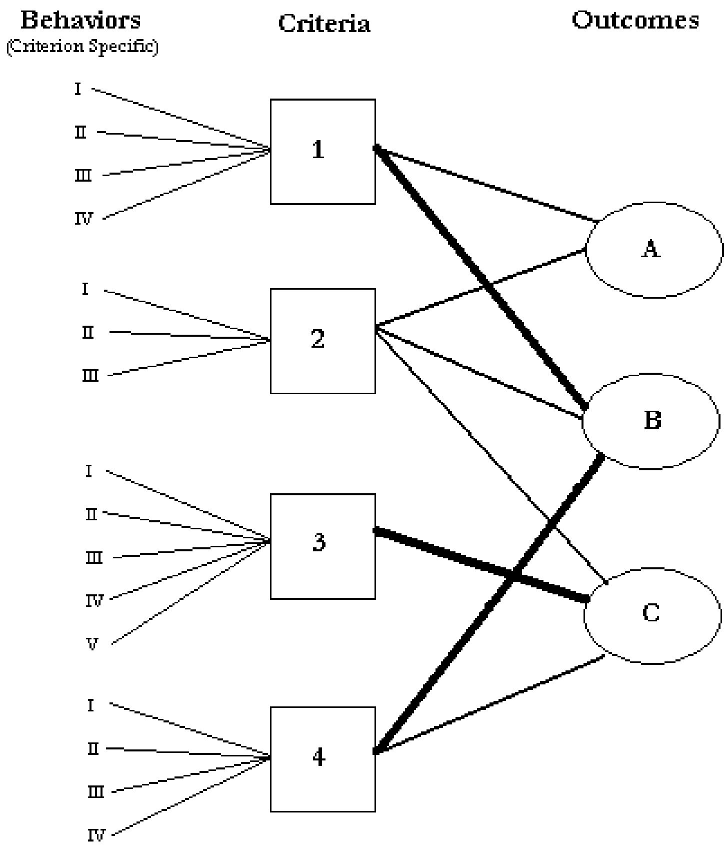

Figure 5: Representation of the interaction between Behaviors, Criteria and Outcomes

Each criterion has associated behaviors, varying from five to nine in number, depending upon the criterion. The eight outcomes are identified by letters A-H; the eleven criteria are numbered 1-11; and the behaviors within each criterion are referred to using Roman numerals. The student's mark for a criterion is simply the number of associated behaviors displayed in his or her report. Neither which of the behaviors are included, nor where the behaviors appear in the report matter. This fine-grained approach to marking the reports reduced the potential confounding impact of the marker. Marking is a digital yes-no process rather than a continuous "feels like seventy percent" approach.

The lab class is intended to produce eight learning outcomes – three that are task-specific, and five that are generic skills usually associated with third year engineering students.

Specific Outcomes:

A) Appreciation of the hardware involved

B) Reasons for calibration

C) The complexity of signals

Generic Skills:

D) Identification of Assumptions

E) Exception handling

F) Processing of data

G) Limitations of accuracy

H) Comparison of data

These outcomes are measured as linear combinations of the criteria marks. The links between criteria and their related outcomes are shown in Table 1.

Table 1: Criteria - Outcome linkages

No.	Criterion	Outcomes
1	The relationship between $H(\omega)$ and ω	**F**
2	The Calibration Constant A (Final Value)	F,**G**
3	The Calibration Process	C,F,H
4	Deviation from the 'ideal' $H(\omega)$ vs ω straight line response	E,F
5	Assumptions involved in simplifying the transfer function	**D**
6	Linearity of the Accelerometer system	C,**H**
7	Resonance / Anti-resonance pair	**E**
8	The Piezoelectric Accelerometer	**A**
9	The laser Doppler System	**A**
10	Calibration as a process	**B**
11	Spectral Analysis	A,**C**

The **bold** letters indicate strong relationships, which were weighted twice as heavily in determining the outcome score. From these relationships values for the eight different outcomes were determined for each student.

Students' learning styles

Students have preferences about how they prefer to learn – how they prefer to receive and process new information. If methods of instruction match their preferences, then they are more effective learners. The constructivist paradigm suggests that the interaction of separation from the hardware and a technology-mediated interface to close this distance will change the nature of the learning enviroment (Lindsay et al. 2007). The students' preferred learning styles will further impact their learning outcomes by influencing how they interact with this environment, and how they assimilate the laboratory into their prior learning.

This study makes use of the Felder-Solomon Inventory of Learning Styles (ILS) (Felder and Solomon). The ILS distinguishes four dimensions:

- Active – Reflective
- Sensing – Intuiting
- Sequential – Global
- Visual – Verbal

Each of these dimensions is measured through a series of questions in which students select from two responses that characterize them along one of the dimensions.

Each student was asked to complete the ILS, however the response rate was less than 100%. Responses on the ILS were matched to the marks for the learning outcomes, with incomplete matches excluded from the study. This left a total of 86 data points with complete learning outcome and learning style information, distributed between modes according to Table 2:

Table 2: Distribution Among Modes

Mode	Data Points
Proximal	31
Remote	27
Simulation	28

The learning styles distributions appear to somewhat follow the normal distribution, but there are some biases in the means (Figure 6). The cohort is strongly biased towards visual learners, as well as displaying a bias towards sequential learners.

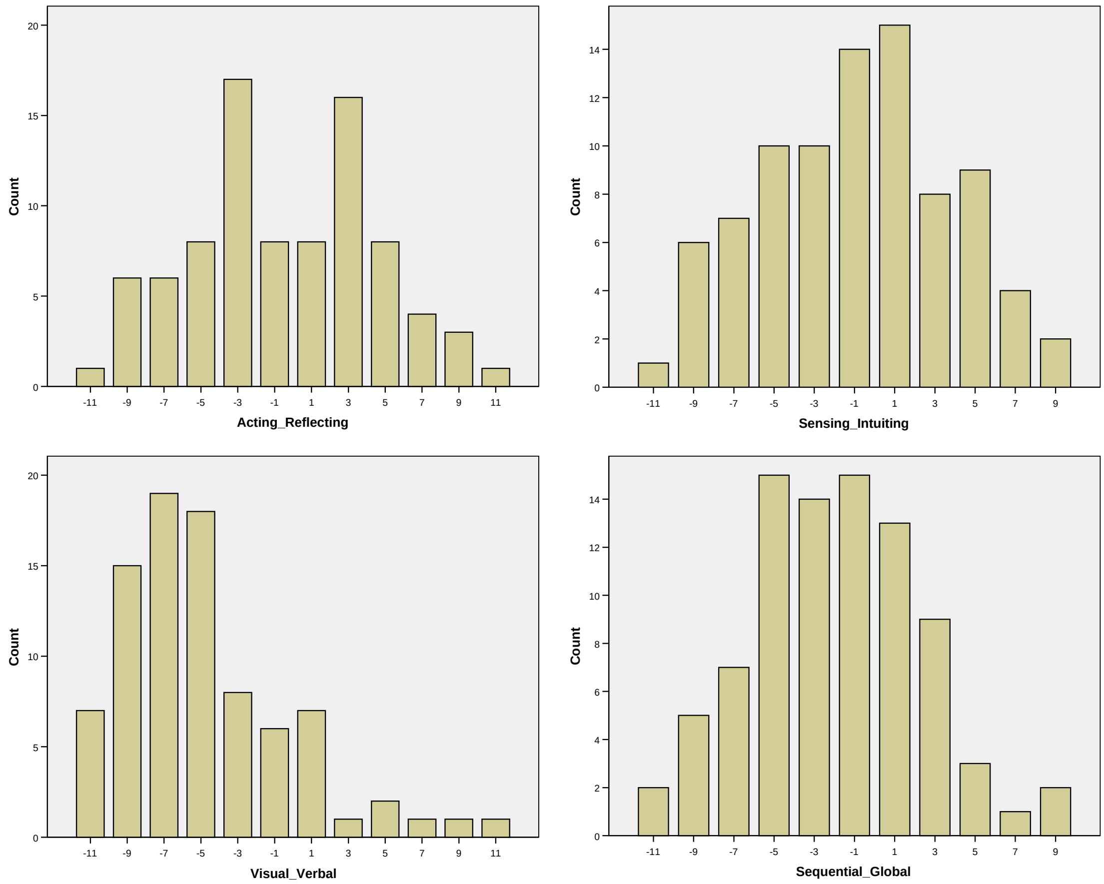

Figure 6: Distribution of Learning Styles

To simplify the analysis, the distributions of students in each learning style were aggregated into three categories: Those who scored 5 or higher in either direction were aggregated into a group representing that extreme of the style, whilst those who scored 3 or less in either direction were aggregated into a neutral group for that style. Figure 7 shows these aggregated categories for each learning style dimension, along with the distribution amongst the three modes:

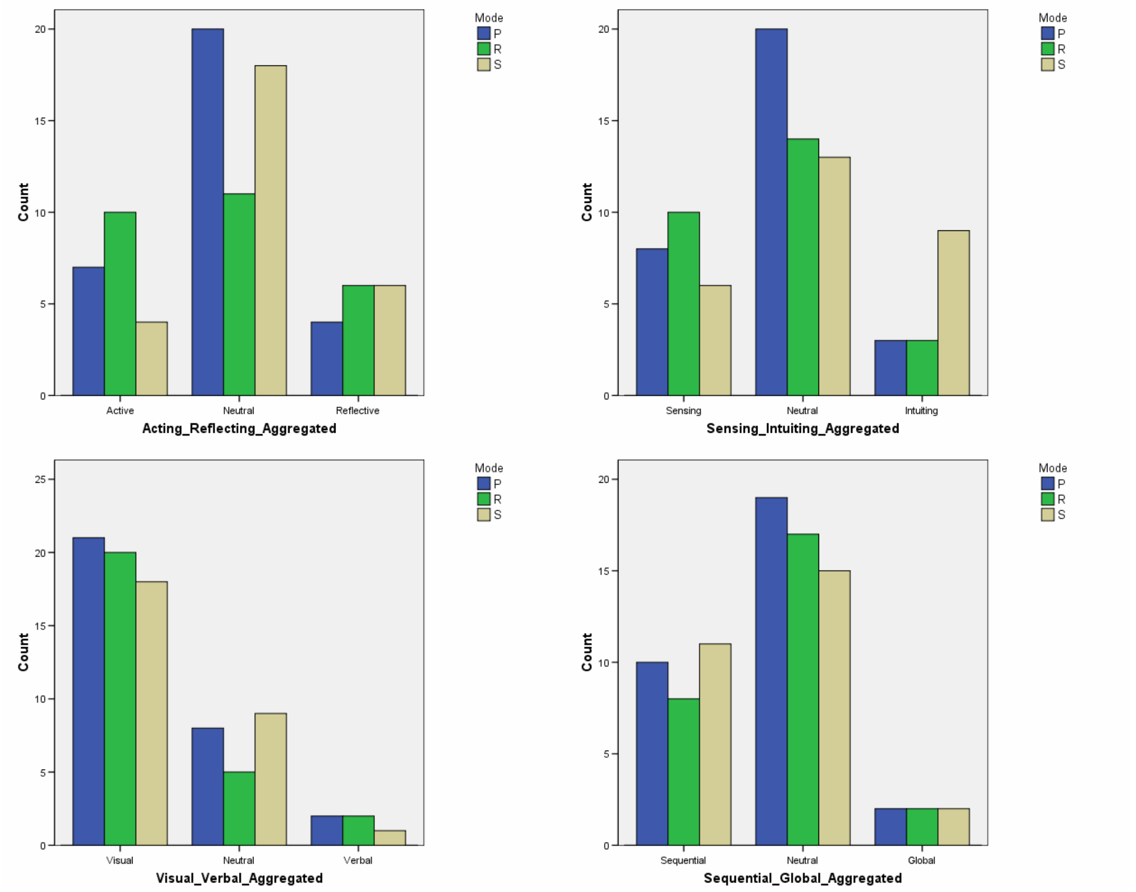

Figure 7: Aggregated Learning Style Distributions

Figure 7 shows that the distribution of the learning styles across the modes is relatively even – each of the categories is represented in each of the modes, mostly in similar proportions. Contingency table analysis (McNemar 1969) shows that only the Sensing-Intuiting dimension differs significantly from an equal distribution, due mostly to the prevalence of the simulation mode amongst the intuiting learners.

Simple ANOVA Analysis

Four sets of ANOVA analyses were performed to investigate the interaction between the access mode and each of the four learning style axes in turn. The analysis was performed for all eight learning outcomes for each of the learning style dimensions.

The ANOVA analyses found a total of six significant results. Four of these significant differences were purely upon the mode, and not any interaction with learning style. These were for Outcomes E (Exception Handling) and G (Limitations of Accuracy), which are consistent with what has previously been found to be dependent upon the mode (Lindsay and Good 2005). Two of the significant results showed dependency upon both mode and learning style.

The two remaining significant dependencies were the interaction between the Sensing-Intuiting scale and Mode for Outcome D (p=.048), and the interaction between the Acting-Reflecting axis and Mode for Outcome C (p=.031). To investigate these significant ANOVA results in more depth, the means for outcome were plotted in a line graph, with a separate line for each mode.

Figure 8 shows a clear difference in the effect of Sensing-Intuiting learning style upon Outcome D, Identification of Assumptions, for the different access modes. The proximal and simulation modes display similar tendencies, albeit with an apparent degradation in performance on the part of the simulation mode. Students who are Intuiting or Neutral learners perform similarly, whilst students who are Sensing learners perform less strongly on this outcome.

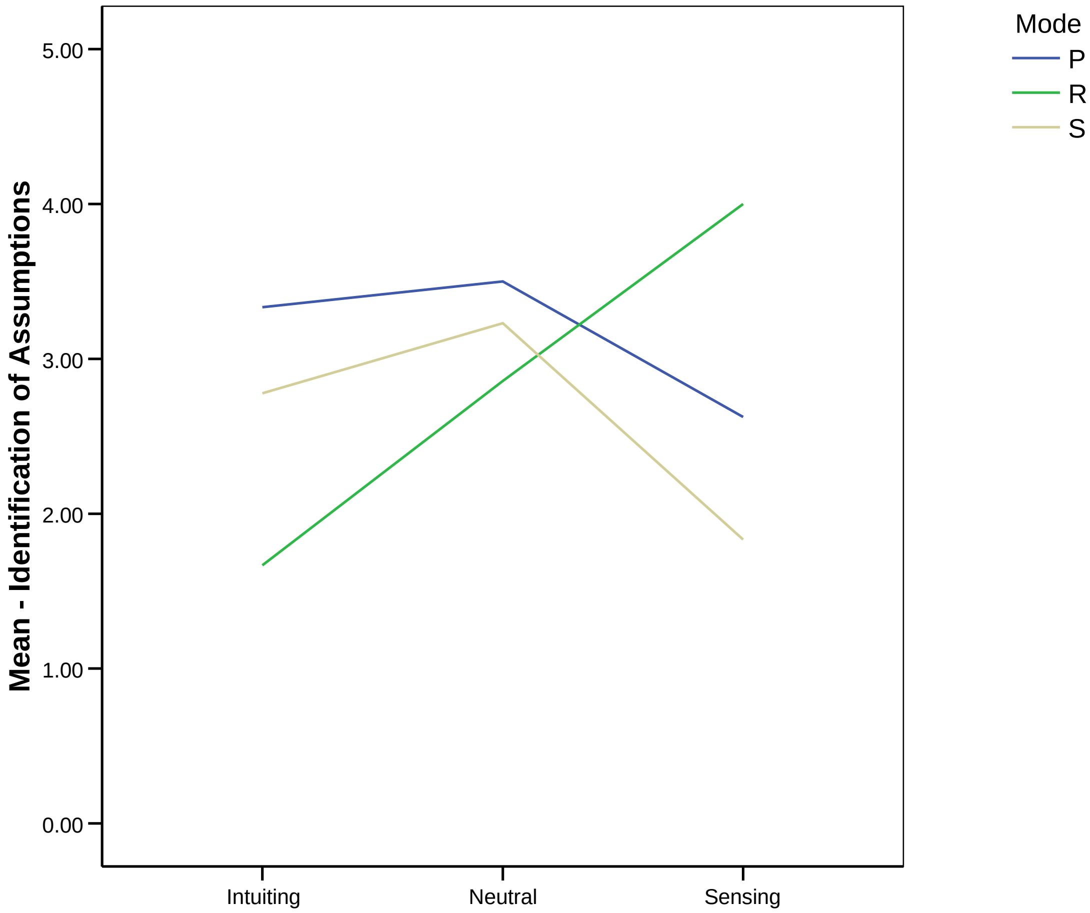

Figure 8: Outcome D – Identification of Assumptions vs S-I scale & mode

For the Remote mode, there is a clear link between the students' learning style and their outcomes. For students who prefer an Intuiting learning style, the remote mode underperforms both of the alternatives. For students who prefer a Sensing learning style, however, the Remote mode leads to an improvement in the student's performance – indeed, it is the only mode where Sensing learners outperform Intuiting or Neutral learners.

For the purposes of Outcome D, Identification of Assumptions, it is clear that for Sensing learners, the Remote Mode is the most effective form of access, whilst for Intuiting and Neutral learners, it is the proximal mode that leads to the strongest learning outcomes.

Figure 9 shows that there is a relationship between Acting-Reflecting learning style, mode, and Outcome C, Complexity of Signals. Unlike the relationship for Outcome D above, however, the two variables cannot be decoupled – the outcome is dependent upon the interaction of both.

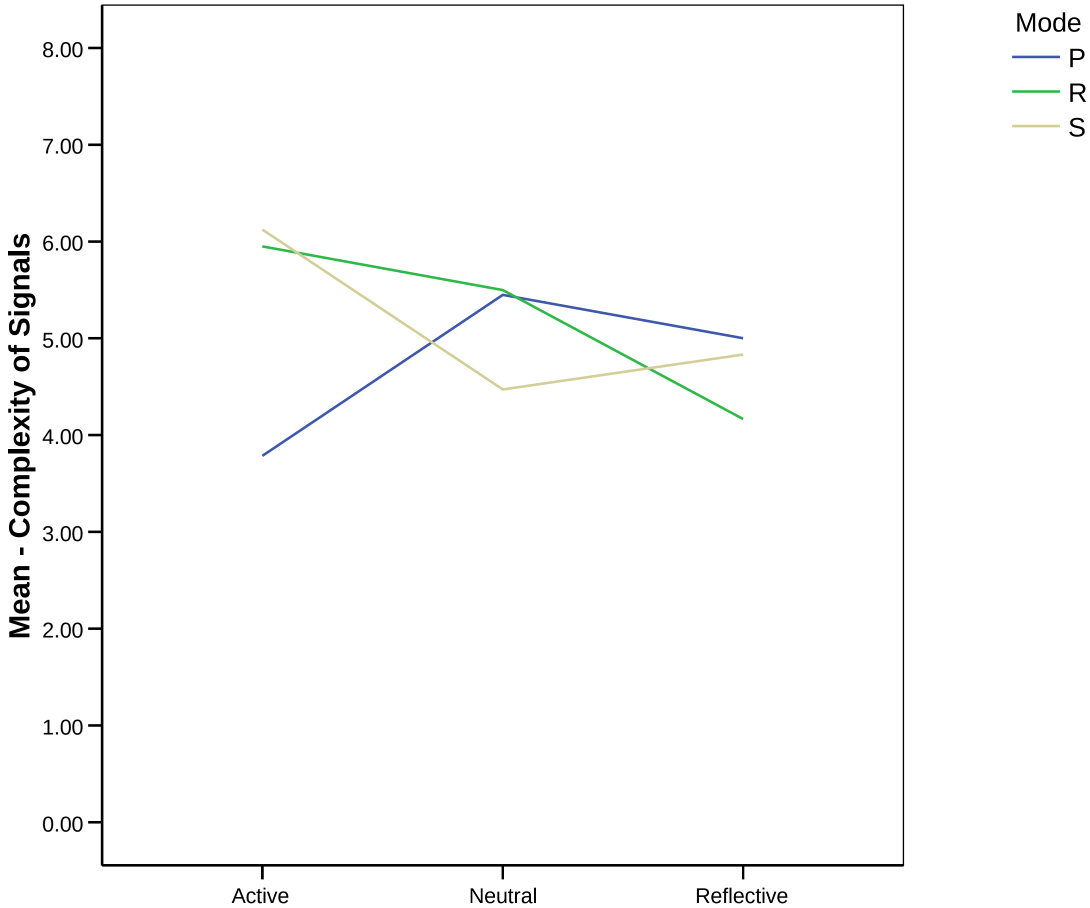

Figure 9: Outcome C - Complexity of Signals vs A-R scale & mode

ANOVA analysis indicates when there are significant dependencies occurring, but with more than one independent variable, post-hoc testing cannot be used to determine which variables are causing these significant dependencies.

To overcome this problem, four new variables were created – combining each of the learning style axes with the mode. Thus, rather than nine combinations of two three-level variables, a new nine-level variable was created. This also allowed for comparisons to be made between cells that do not share a learning style or mode, ie Active Proximal vs Reflective Remote.

Revised ANOVA – Combination Variables

The shift to the combination variables was complicated by the nature of the data points. Undergraduate engineering cohorts display substantial biases in their learning styles, and with an overall cohort size of 86, this led to some cell sizes that were unusable. Only six of the cohort were Global learners, and whilst they were evenly spread amongst the three access modes, two data points per cell does not allow meaningful analysis. Similarly only five of the cohort were Verbal learners, leading to cell sizes of two, two and one for the three modes.

The Proximal-Intuiting and Remote-Intuiting cells both contained only three data points. The Simulation-Intuiting cell, however, contained nine data points, allowing the possibility of meaningful comparisons. As such, the threshold for minimum number of data points was set at three.

Four ANOVA analyses were performed for each of the eight Outcomes – Active-Reflective-Mode and Sensing-Intuiting-Mode with a nine-level combined variable, and Visual-Verbal-Mode and Sequential-Global-Mode with a six level combined variable. These ANOVA analyses yielded four significant and three nearly significant differences:

Outcome E – Exception Handling

Proximal-Visual vs Simulation-Visual p = .047*

Proximal-Visual vs Remote-Visual p = .060

Outcome G – Limitations of Accuracy

Proximal-Sensing vs Simulation-SI-Neutral p = .018*

Proximal-VV-Neutral vs Simulation-VV-Neutral p = .079

Remote-Visual vs Simulation-VV-Neutral p = .062

Proximal-Sequential vs Simulation-SG-Neutral p = .036*

Remote-SG-Neutral vs Simulation-SG-Neutral p = .003*

Both of these outcomes also showed significant differences in the first ANOVA analsyis, as well as showing significant differences when the mode alone was considered (Lindsay and Good 2005).

The style-wise breakdown of both of these outcomes were investigated for all four styles (Figure 10 and Figure 11). Previously reported studies (Lindsay and Good 2005) also found statistically significant differences between the modes for both outcomes E and G for the overall cohort. If these differences were truly independent of learning style, then Figure 10 and Figure 11 would consist of three parallel, horizontal lines, with the distances between these lines representing the difference in outcome caused by the mode.

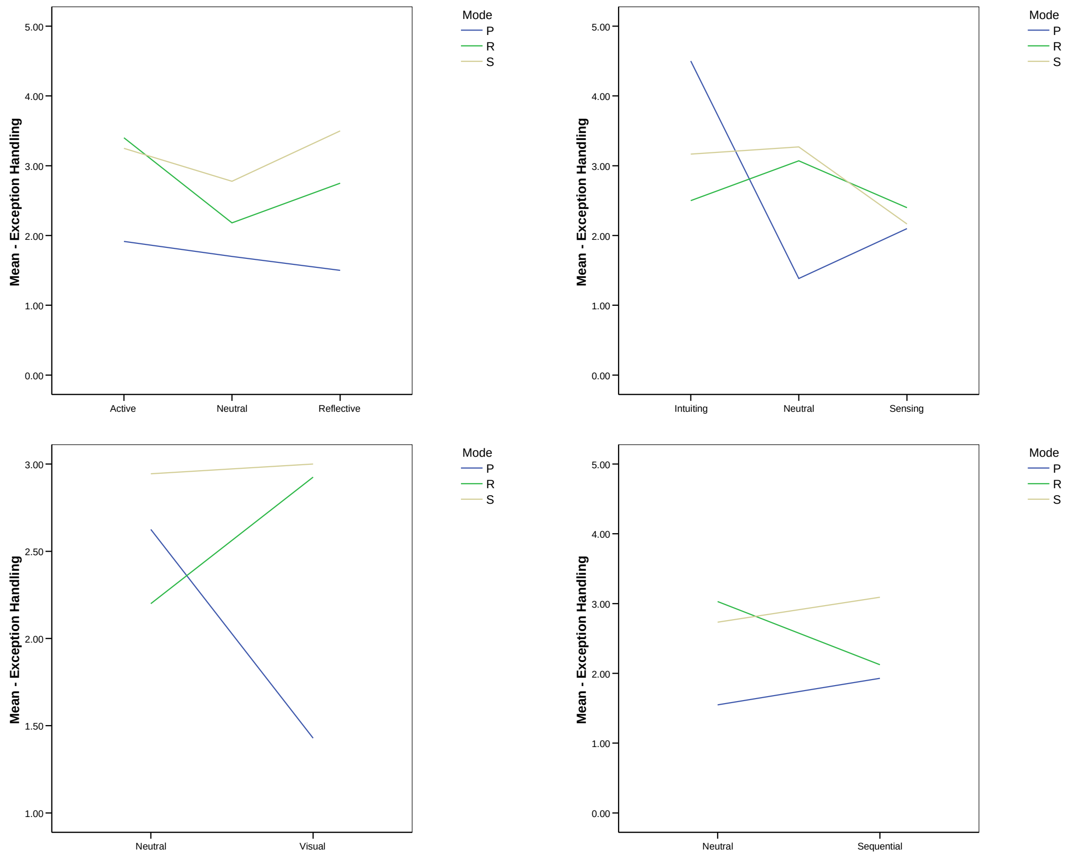

Figure 10: Learning Style Variations within Modes - Outcome E, Exception Handling

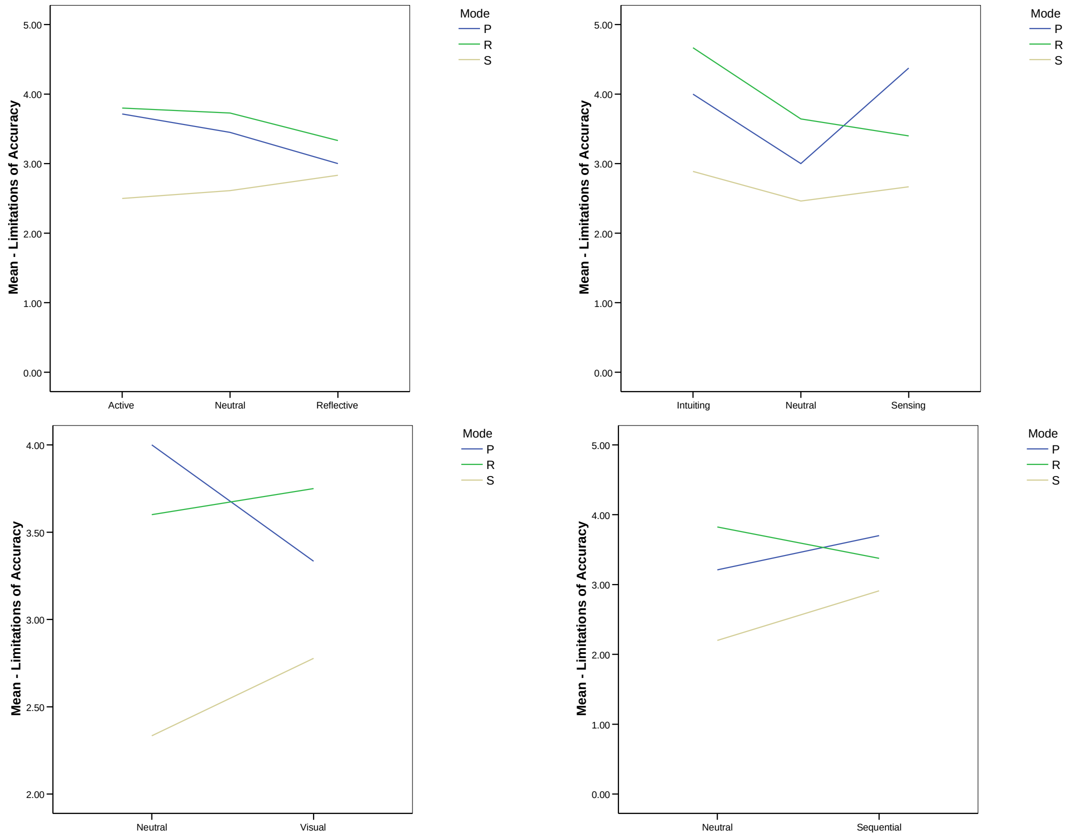

Figure 11: Learning Style Variations within Modes - Outcome G, Limitations of Accuracy

Figure 10 and Figure 11, however, do not show this pattern. Many of the plots show similar trends in two of the three modes, but the line for the third mode slopes in a different direction. Whilst the differences in slopes have not been shown to be statistically significant, it is nonetheless indicative that there is an interaction between learning style, mode and outcomes. For some instances a gain or a loss is exacerbated in a switch between modes, where in others students perform no differently in an alternative mode.

Conclusion

The previous analysis of this data showed that there were some significant differences between the learning outcomes of students exposed to the different laboratory access modes. This deeper analysis suggests that these differences are in fact also dependent upon the students' preferred learning styles. Whilst the phenomenon is not universal – there are learning outcomes which appear unaffected by access mode or learning style – there are significant interactions in some cases, and clearly indicative trends emerging.

The analysis raises more questions regarding the way in which students construct their learning in the laboratory context. Whilst the evidence suggests that there is a relationship between access modes, preferred learning styles and learning outcomes, it does not provide insight into the causes of these interactions. Is it a matter of the mode forcing students into a particular learning style, and those for whom this style is dispreferred find their learning degraded? Or is it that a particular learning style is better able to take advantage of the experience offered by a particular access mode? Further investigation – with larger cohorts, to allow for greater statistical power – is necessary.

This study suggests that there is an interaction between access modes, preferred learning styles and learning outcomes. Learning styles can potentially be used as a diagnostic tool to tailor the choice of access mode to the student if multiple modes are available. Alternatively, they can be used to focus the scaffolding for the experience, if the choice of mode is fixed. More importantly, the design of future remote and virtual laboratory classes must ensure that learning styles are accounted for to ensure that students' opportunities are maximized.

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