International Journal of Engineering Education Vol. 28, No. 4, pp. 920–931, 2012
Printed in Great Britain
0949-149X/91 $3.00+0.00

The Power of Pull in Engineering Student Learning*

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Biggs' Study Process Questionnaire is used to measure the constructive alignment of student choice with deep and shallow approaches to learning in established undergraduate and postgraduate engineering subjects designed for pull-learning, in contrast to push-teaching. Dividend output factors of increased student marks are established for a deep approach to learning and the inverse of a Shallow Approach to learning. Empirical Bayesian analysis comprising Exploratory Factor Analysis and Bayesian Confirmatory Strategies is used to deeply mine and draw inferences from relatively small sample sizes. This research confirms Biggs' suggestion that the tendency of education to erode towards Shallow Learning may be addressed through curriculum design that constructively aligns student choices with deep engagement. Students in subjects designed for pull-learning do appreciate the constructive alignment of their choices with deep engagement. Furthermore, there is a dividend payoff in marks for both deep engagement and the opposite of shallow engagement. The findings provide considerable optimism for the development of pull-learning techniques to increase the generic work-ready skills of graduate engineering students.

Keywords: Biggs Study Process Questionnaire; Empirical Bayes; Bayesian Confirmatory Factor Analysis; electronic portfolio; eportfolio

1. Introduction

From their discipline subjects, students learn core input knowledge and skills in topics such as structures or circuits and repeatable methodologies for domain specific problem solving. However employers seek work-ready graduates where core knowledge is augmented with generic graduate attributes developed through engagement in real world output focused projects and exposure to multifaceted professional learning in the workplace. Such tacit learning tends to occur in edge subjects where flows of knowledge are experienced rather than in the core discipline subjects devoted to the store of knowledge. For example, learning to manage flows of knowledge is inherent in outbound multidisciplinary projects and practice or intern programs designed so that emotional intelligence flourishes as students use their personal intuition, creativity, entrepreneurship and collaborative abilities to meet real world demands [1 pp. 49–56].

As with managers in the workplace, the most important outcome from an edge project is the delivery of a realistic solution on time and budget. The problem may be quite complicated, for example in an area of complex human behaviour, an emerging industry niche or cross-disciplinary domain. It is from such activities that new knowledge often evolves. This new knowledge can percolate towards the core where it consolidates into newly formalised teaching [1 pp. 56–7]. The speed with which edge knowledge gravitates to the core may be very rapid as seen with social networking [2] and the 1992 Pathfinder project study of genetic inheritance [3] that burgeoned into applications for machine learning and probabilistic graphical networks that are now commonplace in diagnostic systems and Internet search engines. In the same way, undergraduate and postgraduate knowledge created through edge projects percolates to the core through many avenues. Research supervision and research-informed teaching are the most apparent routes. However, another primary route is that the up-skilling of students through edge projects provides an opportunity for teaching even more advanced materials in subsequent edge subjects.

Students experience quite deep emotional events in real world projects due to the stress of dealing with outside parties and their peers. It is the subject coordinator's task to ensure that students can make mistakes safely so distress is minimised. Such hard-won professional enlightenment warrants proper consolidation through a formal cognitive process of reflection on the relationship between mistakes and unprofessional beliefs that adequately deals with student psychological dissonance. Student engineering identity research has shown that the formal consolidation of experiences in such portfolios assists students to develop a professional self-narrative and make sense of the world [4]. In addition to contributing to the development of self-esteem and confidence, such a portfolio provides a log of personal growth experiences and learning across graduate attributes to recount at appropriate times, such as in the context of employment.

For more than three decades educationalists have looked to taxonomies for structuring beliefs and values in subject design [5]. These heuristic design guides for higher order behavioural outcomes facil-

* Accepted 25 March 2012.

itate the design of assessment tasks and classification of student performance. The well-known Bloom's Taxonomy of Educational Objectives [6] and Biggs' Structure of the Observed Learning Outcome (SOLO) [7] are sets of transformations to performance level goals in a strictly hierarchical framework similar to that of Maslow [8]. Furthermore, the intensifying industry and government expectations of graduate employability have led educators to expand their focus toward mature generic skills in order to enhance graduates' 'work-ready' capacities [9–11].

An underlying assumption in the universality of these taxonomy-based learning heuristics is that any well designed subject will generate the desired student behavioural outcome. Therefore educators have often implemented these taxonomies together with student graduate attribute development across the whole curriculum, including core knowledge subjects that represent the majority of subjects in the curriculum [12–14]. Professional discipline lecturers often perceive with understandable discomfort their institution's increasing emphasis on developing student graduate attributes in core knowledge subjects or through increased edge subjects with underlying liberal and humanities frameworks. In many institutions the balance of course real-estate devoted to core discipline and edge subjects remains an impassioned discussion.

The importance of taxonomic design also needs to be balanced with Sheull's student-centric focus that 'what the student does is actually more important in determining what is learned than what the teacher does' [15 p. 429]. Biggs [16] highlights that students make choices to engage or otherwise in learning, based across multiple contexts. He maintains that the teacher's task is to deliver subjects in a way that constructively aligns such student's choices to Deep Approaches in learning. Biggs' calls on institutions, subject co-ordinators and lecturers to deliver stimulating subject structures that facilitate student learning both inside and outside the classroom. In order to measure student choices of Deep Approaches over Shallow Approaches, and from this to evaluate the success of teachers and teaching strategies, Biggs and his colleagues developed two questionnaires: the Study Process Questionnaire [17] for university education and the Learning Process Questionnaire [18] for secondary education. Biggs and Tang [19] teaching and learning design manual is based on this questionnaire research and experiments with portfolio based assessment.

This research seeks to evaluate student motivation and the development of graduate attributes in university subjects specifically designed for pull-based learning. The research is based on five years of experience in the use of reflective portfolios [20] in two subjects designed for pull-learning congruent with recent formulations for the 'Power of Pull' in social networking theory for society and business [1].

In the two subjects investigated in this research, self-development and professional career building is as important as the baseline knowledge and skills acquired. These edge or output based subjects involve student self-learning and realisation. Students learn from their peers as much as their teachers and complete projects involving diverse techniques and roles across real world based assignments, life-like simulations and case studies.

Many researchers have examined the factor structure of Biggs' Study Process Questionnaire, including Biggs *et al.* [17] following shortening of the questionnaire. However these studies do not address whether constructive engagement with deep learning results in higher grades. Rather it remains an implicit assumption in the Study Process Questionnaire.

The original contribution presented in this research is to answer the question of whether there are Dividend Output Factors of higher student marks for a Deep Approach to learning and the inverse of a Shallow Approach to learning in subjects designed specifically for pull-learning.

2. Methodology

2.1 Data collection

Data were collected from two subjects across the 14 week academic semesters Spring 2010 and Autumn 2011. The subjects were undergraduate Engineering Economics & Finance (referred to below as groups ug1 and ug2) and postgraduate Value Chain Engineering Systems (referred to below as groups pg1 and pg2). The former subject nominally has 300 students and the latter 40 students.

The same subject coordinator/lecturer manages each subject and the same teaching techniques are used, although the material is different. In each subject the students are assessed on two major projects (25% of subject mark each), a formal written electronic portfolio of reflections based on a cognitive therapy model (15% of subject mark) and a multiple choice question examination (35% of subject mark).

The first of the two major projects is to visit an external company and undertake either an Enterprise Resource Planning systems demonstration (undergraduate) or Business Process redevelopment project (postgraduate) in a group of six students and make a video of the engagement. This video is assessed for a group component of the mark while individual cognitive reflections are assessed for an individual component of the mark.

The second of the two main projects is a competitive on-line business simulation game played by groups of three students [21]. As with the first project, this game is assessed with group performance components, individual components such as quizzes and self and peer review, and individual cognitive reflections.

A formal written electronic portfolio comprises cognitive reflections from each of the two major activating experience assignments. As the aim of written cognitive reflections is to reinforce students practice in the techniques of professional reflection, there is scope to enhance the written electronic portfolio with supplementary cognitive reflections across work, internship and co-curricular activities.

During the semester, students are asked to complete a twenty question Biggs' Study Process Questionnaire [17]. This survey about study attitudes is not anonymous because comment on a generic theme is not a potentially sensitive issue, as would be a personality test or satisfaction survey. Students readily accept that the survey does not influence their subject mark in any way other than a fixed four mark reward for successful completion of the survey. Many students see the bonus marks as a measure of insurance in achieving the grade they hope to achieve in the subject. In any case, most students are found to be reasonably pragmatic and direct in such matters because the Faculty immerses students into the practice based learning paradigm early in their studies and most will have either engaged in internships or plan to do so.

As a consequence, the most efficient approach for students is quickly to answer the brief survey at face value rather than to think too much about the questions and to ponder and decide which of their many 'selfs' will be presented to the survey. The students readily have at hand quite strong responses as they have just submitted the first of their two major projects including cognitive reflections. It is found that over 85% of students complete the survey.

2.2 Data analysis

In the last few decades it has become increasingly popular to use an Empirical Bayes approach to analyse smaller sets of data [22, 23, 24 p. 134]. An Empirical Bayes approach is used in this research by conducting Bayesian Confirmatory Strategies based on the findings of the Exploratory Factor Analysis phase.

There two reasons to move beyond Exploratory Factor Analysis to confirmatory strategy. The first is that maximum likelihood factor analysis may produce anomalous results with small sociological samples (for an example, see Appendix Table 2, Note 6). Exploratory Factor Analysis is best suited to very large data sets with relatively strong trends. For reliability, the size of these samples ranges from many hundreds to many thousands of cases. This contrasts to sample sizes in this research of approximately 260 in each undergraduate group, with only 34 cases in the first postgraduate group and 38 in the second postgraduate group.

A second reason to move beyond the first phase of an Exploratory Factor Analysis to a Bayesian Confirmatory Strategy is the unconditional methodological requirement in the use of Fisher's p-values 'to regard observations as a basis for possibly rejecting hypotheses, but in no case for supporting them' [25]. In Exploratory Factor Analysis, this introduces a desirable pessimistic bias to help guard against bad decisions being made on the basis of simplified models of reality [26 p. 2].

In contrast, the Bayesian perspective looks to make the best possible use of inferences from limited data. For example, researchers may prefer to establish which of their models is more likely given the data rather than to test whether a hypothesis should be rejected or not [27]. Bayesian analysis retains conservative practice through restrictions on the interpretation of the results. Instead of outcomes being regarded as generally applicable principles derived from large scale population studies, the outcomes are regarded as being conditional upon the current data and circumstances. This introduces assurance requirements of a well understood domain where data are collected under the supervision of a domain expert.

The first phase of the Empirical Bayes analysis is to investigate latent factors through Exploratory Factor Analysis. This phase has four analysis items. Item 1 is to investigate the relationship between the Biggs Survey Question responses and Biggs' component meta factors (DM, DS, SM and SS). Item 2 is to investigate the correspondence of these component meta factors with Biggs' aggregate meta factors for the Deep Approach (DA) and Shallow Approach (SA). Items 3 and 4 are to investigate potential Deep Approach (DA) and Shallow Approach (SA) Dividend Output Factors latent in the relationship between Subject Mark and Biggs' component and aggregate meta factors respectively.

The second phase of the Empirical Bayes analysis is to investigate latent factor models through Bayesian Confirmatory Strategies. This phase has three items. The first is to repeat Item 2 (above) in a Bayesian framework to confirm the independence of Biggs' Deep Approach (DA) and Shallow Approach (SA) aggregate meta factors.

The second part of the Bayesian Confirmatory Strategy is to prepare and evaluate Bayesian Dividend Output Factor models that embody common conditioned prior distributions suggested by the Exploratory Factor Analysis. The two prior conditionings suggested by the Exploratory Factor Analysis phase are independent Deep Approach (DA) and Shallow Approach (SA) factors and an inverse Shallow Approach (SA) related Dividend Output Factor of a return in Subject Mark from the inverse of a Shallow Approach (SA) to learning.

Key differences in conditioning priors are introduced across three Bayesian Dividend Output Factor models: Model 1 loads Subject Mark negatively to the Deep Approach (DA) Dividend Output Factor; Model 2 loads Subject Mark positively to the Deep Approach (DA) Dividend Output Factor (i.e. the virtuous assumptions model); and Model 3 excludes any loading of Subject Mark to the Deep Approach (DA) Dividend Output Factor.

The final part of the Bayesian Confirmatory Strategy is to compare the Bayes factors of the three Bayesian Dividend Output Factor models to determine the preferred model of return for effort in a Dividend Output Factor. Bayes factors are the plausibility ratios of the marginal likelihoods resulting from Bayesian regression of the scores of the Dividend Output Factors to the Deep Approach (DA) and Shallow Approach (SA) aggregate meta factors and Subject Mark data.

The above models include the common prior assumption of an inverse Shallow Approach (SA) related Dividend Output Factor of a return in Subject Mark from the inverse of a Shallow Approach (SA) to learning. As part of Methodology assurance in this final analysis phase, the Bayes factors for the reverse conditioning assumption of a Shallow Approach (SA) related Dividend Output Factor of a return in Subject Mark from a Shallow Approach (SA) to learning is tested with Models 1 to 3 to confirm that the reverse assumption is significantly inferior to the common prior assumption suggested by the Exploratory Factor Analysis.

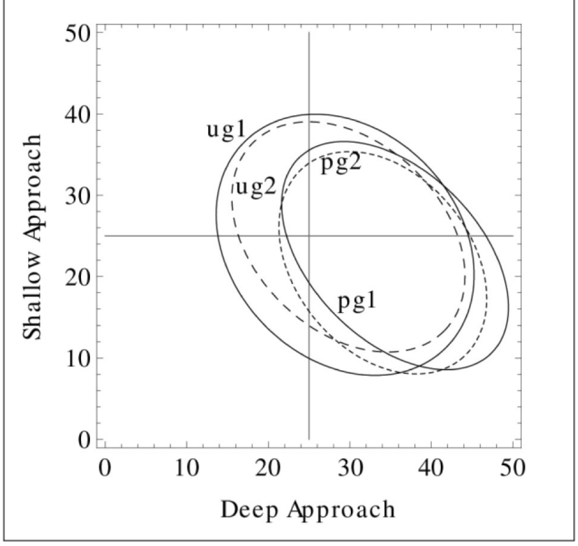

Fig. 1. Shallow Approach vs. Deep Approach to learning for undergraduate (ug1, ug2) and postgraduate (pg1, pg2) student groups, shown as a comparison of the 95th percentile ellipses for bivariate data.

3. Results

3.1 Data

The calculated Biggs' aggregate meta factors for Deep Approach (DA) and Shallow Approach (SA) to learning are shown in Fig. 1 as 95th percentile ellipses for undergraduate (ug1 and ug2) and postgraduate (pg1 and pg2) student groups. It may be noted that the centre of gravity for the Deep Approach (DA) is moderately high in all undergraduate and postgraduate groups.

Student Subject Mark is shown as a function of Biggs' aggregate meta factors in Fig. 2. Students tend to occupy the desirable top-right quadrant where both Deep Approach (DA) to learning and Subject Mark are moderately high.

Figure 2 also shows student Subject Mark as a function of Biggs' Shallow Approach (SA) to learning. It may be noted that the Shallow Approach (SA) to learning is mid-range compared with moderately high for the Deep Approach (DA) aggregate factor.

Notwithstanding consistent static results for the two postgraduate groups, rotation of the pg2 ellipse for Subject Mark with Deep Learning from the expected pg1 orientation suggests the presence of some dynamic variability at higher levels of Deep Learning.

3.2 Exploratory factor analysis

Exploratory Factor Analysis is the first of the two phases of Empirical Bayesian analysis. It extends the static observation of data relationships (above) to an investigation of the dynamic underlying factors. The results are provided in the Appendix, Table A1. The main observation from Data Analysis Items 1 to 3 is that aggregate output factors such as the Biggs' aggregate meta factors (DA, SA) are strongly indicated in contrast to the lower level component meta factors (DM, DS, SM, SS).

The synthesis of Biggs' component meta factors (DM, DS, SM and SS) with Subject Marks in Data Analysis Item 3 is inconclusive using a loading cut-off of 0.6. Bayesian confirmatory strategies are pursued instead of rationalising a lower cut-off, of say 0.4. However, it may be noted that at lower cut-offs there are indicative higher order Dividend Output Factors of reward for a Deep Approach (DA) to learning and the inverse of a Shallow

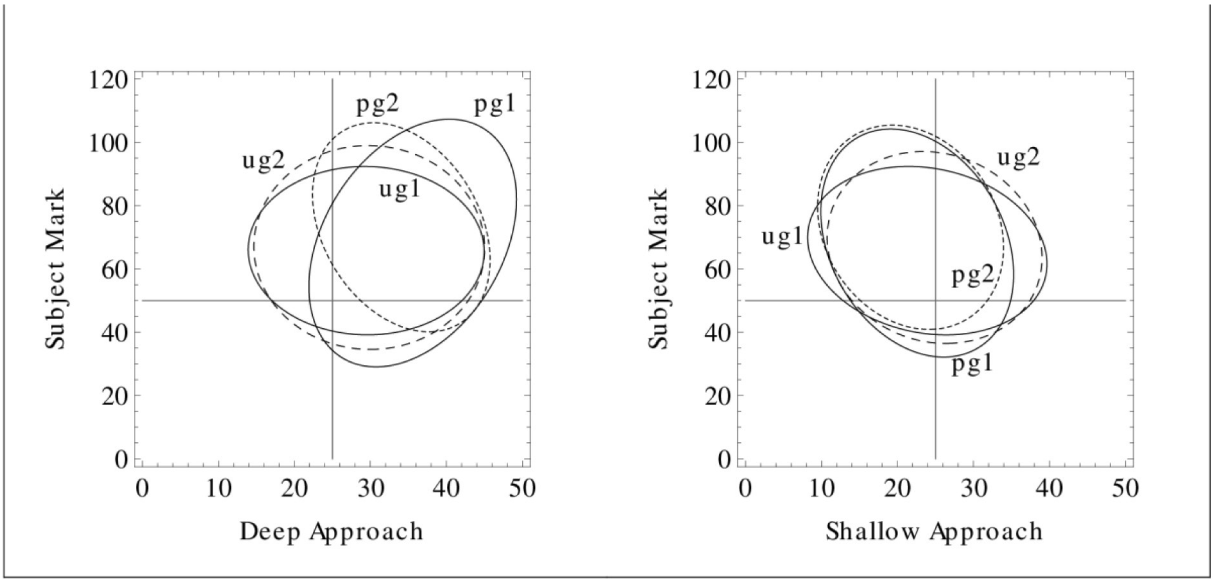

Fig. 2. Subject Mark vs. Deep & Shallow Approaches to learning for undergraduate (ug1, ug2) and postgraduate (pg1, pg2) student groups, shown as a comparison of the 95th percentile ellipses for bivariate data.

Approach (SA) to learning. Notwithstanding this, in what may be an example of anomalous results from small sample sizes, postgraduate Deep Approach (DA) to learning indications are contradictory.

In Data Analysis Item 4, the Biggs' aggregate meta factors (DA, SA) merge into a net DA-SA output factor that obscures Deep Approach (DA) and Shallow Approach (SA) Dividend Output Factors. In the two class groups where the Deep Approach (DA) and Shallow Approach (SA) factors are distinct, Subject Mark loads weakly with Deep Approach for one postgraduate class (0.32) and inversely with Shallow Approach for one undergraduate class (–0.38).

The lacklustre conclusiveness of the Exploratory Factor Analysis is reflected in Cronbach's Alpha and McDonald's Omega indices of reliability, which are not simultaneously satisfactory in any group.

3.3 Bayesian confirmatory strategy

Bayesian confirmatory strategies are able to bring considerable additional perspective to the identification of latent factors. The Bayesian Confirmatory analysis of Biggs' component meta factors (DM, DS, SM, SS), provided in the Appendix, Table A2, identifies very strong loadings for the Biggs' component meta factor loadings of 0.8 (and more) to the independent Biggs' aggregate meta factors (DA, DS). This finding confirms the Exploratory Factor Analysis phase indications that Biggs' aggregate meta factors (DA, DS) may be used to condition the prior distributions in Dividend Output Factor models.

3.3.1 Confirmatory analysis of loading of subject marks to aggregate meta factors

The results for the three Bayesian Confirmatory Strategy models are summarised in the Appendix, Table A3. The strength of factor loadings is satisfactory although not subjected to an arbitrary cut-off as in the Exploratory Factor Analysis phase.

It may be noted that results for postgraduate groups are reliable in all three models. However, results for the undergraduate groups are only partially reliable. While the models all pass the Heidelberger and Welch's Cramer–von Mises convergence diagnostic stationarity test, the sample size test results for undergraduate groups were weaker than those for postgraduate groups, notwithstanding that the undergraduate groups are a factor of 8 times larger in size.

Bayes factors for pairs of models are shown in the Appendix, Table A4. The Bayes factors indicate a decisive preference for Model 2 over Models 1 & 3. Model 2 is the virtuous assumptions model in which Subject Mark is associated with both a Deep Approach to learning and the inverse of a Shallow Approach to learning.

The Bayes factors for undergraduate groups indicate a very high preference for Model 2. However, the apparent strength of the model preference indicated by such large Bayes factors in undergraduate groups is not as conservatively based as with the postgraduate groups. This is because in undergraduate groups the underlying Bayes Log Marginal Likelihoods from which the Bayes factors are calculated are very large negative logarithmic numbers.

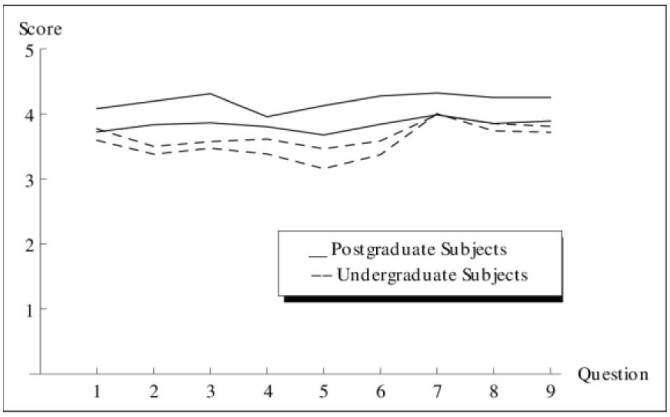

Fig. 3. Results of nine Student Satisfaction Survey questions in two undergraduate classes and two postgraduate classes.

Nevertheless, the consistency of the decisive preference in favour of Model 2 is remarkable across all student groups, though more reliable and demonstrable in postgraduate groups than in undergraduate groups.

4. Discussion

The survey response data plotted in Fig. 1 demonstrated the encouraging feature of students clustering with a moderately high Deep Approach (DA) to learning and mid-range Shallow Approach (SA) to learning. The Exploratory Factor Analysis and Bayesian Confirmatory Strategy phases each confirmed that Biggs' component meta factors (DM, DS, SM, SS) may be used to model students' responses to the Biggs' Study Process Questionnaire and that these component meta factors may be combined into the Biggs' aggregate meta factors (DA, SA).

Although static, Fig. 2 suggested a virtuous assumptions model where Subject Mark is associated with a Deep Approach (DA) to learning and the inverse of a Shallow Approach (SA) to learning. Exploratory Factor Analysis was inconclusive on dynamic relationships, using a conservatively high factor cut-off ratio of 0.6. However, the Exploratory Factor Analysis provided useful indicators to condition the prior probabilities in a Bayesian Confirmatory Strategy. The Bayesian Confirmatory Strategy reinforced a uniformly consistent and decisive preference for the virtuous assumptions model suggested by Fig. 2

The question arises as to why such sensitive Bayesian inference techniques are required to establish the presence of the virtuous assumptions model. This question may be further differentiated into undergraduate and postgraduate issues since postgraduate groups had stronger sample size reliability than undergraduate groups even though the number of undergraduate cases is eight times greater in number than postgraduate cases.

While prospective reasons remain largely speculative, the Student Feedback Survey results shown in Fig. 3 suggest some additional interpretation is possible. Each survey on its own needs to be qualified because participation rates are only 43% for undergraduate and 53% for postgraduate, and there is potential for sample bias. However, comparisons are more meaningful and found to be statistically significant with the null hypothesis that the classes are the same rejected at the 5% level for all questions except questions 7 and 8, which relate to the qualities of the lecturer. This significant difference in satisfaction between undergraduate and postgraduate classes exists notwithstanding that the subject structures are fundamentally the same. This may arise from variations in cultural influences between the predominantly domestic undergraduate students and the much greater international presence in postgraduate studies. Also, the postgraduate students are typically three or four years more mature in age than undergraduate students.

Another speculative possibility that may lead to unreliable self-disclosure of an affinity with a Deep Approach (DA) to learning is students' masquerading of attitudes. Intentional masquerading might be for a student to present their 'self' as having a Deep Approach to learning, whilst this is not indeed the case. However, there is no incentive for this intentional masquerading and there is no indication of a deliberate and widespread strategy of this amongst students.

Perhaps more likely is unintentional masquerading due to student perceptions of the meaning of the Biggs' questions changing over the last decade. There appears to be significant variability in how well questions 'work' with the different class groups resulting in uneven contributions of the questions to the component factors (DM, DS, SM, SS). For example, in each of the first undergraduate and postgraduate groups, factor loadings of 0.6 or greater were found only for two of the ten Deep Approach questions and four of ten Shallow Approach questions.

In the Methodology for data collection it was noted that generally students in practice based engineering courses are found to be reasonably pragmatic and direct in their approach. One possible consequence of this trait is a potential for anomalous responses to some of Biggs' questions. Instead of responding to the positive aspect that the question was originally designed to test, students may have reacted with some aversion to altruistic interpretations. For example Biggs' Question 9 'I find that studying academic topics can at times be as exciting as a good novel or movie' engages postgraduate students but not undergraduate students. One might hypothesise that a movie or games culture is nowadays a serious existential issue in Generation Z peer group values. Similar interpretations of other Deep Approach questions may have led to responses inconsistent with Biggs' original validation of the Questionnaire. Future research might investigate and update Biggs' questions, particularly those related to the Deep Approach.

In addition to the uncertainty arising from students' self-declaration of their Deep Approach or Shallow Approach to learning, this research has a number of other imperfections such as a lack of homogeneity in student groups and a Subject Mark composition that dilutes the accuracy of individual performance measurement with group components. In addition, it is not possible to arrange a control group with the same assessment programme yet without an outputs-based teaching and learning subject structure. While the latter would be desirable, it is noted that four years ago the successful pull-based undergraduate subject in this investigation renovated a push-based subject that had seriously failed.

Though this research environment is less than ideal, the Empirical Bayes approach has inferred interesting and impressive results that support return for effort Dividend Output Factors related to a Deep Approach to learning and the inverse of a Shallow Approach to learning. As one would hope, these findings are in harmony with broader learning theory as well as surviving the reality check of student comments and coordinator and lecturer impressions.

The findings are encouraging for three reasons. The first is that it is undeniably a major achievement to have students at their early stage of professional development clustering in the quadrant of a moderately high Deep Approach to learning and identifying with the inverse of a Shallow Approach to learning. Such a finding is the opposite of the frustration expressed by Biggs *et al.* [17 p. 138] who highlighted in their work and that of others that 'A particularly depressing finding is that most students in most undergraduate courses become increasingly surface and decreasingly deep in their orientation to learning ([16, 28, 29]) something is happening as they progress that is increasingly supporting the use of lower cognitive level activities, which is of course the opposite of what is intended by a university education [28]. One might call it the 'institutionalisation' of learning . . .'. The authors did however confirm that 'There are however exceptions; students with aspirations for graduate study do not show this pattern in their chosen area of study [16], nor do students taught using problem-based learning, who become increasingly deep, and less surface, in their orientations [30].'

A second reason for being encouraged is that these findings support continued investment in pull-frameworks for outputs-based education. These frameworks advance students in their constructive choice of engaging in Deep Learning and facilitate students setting themselves apart from Shallow Learning. Furthermore, the immersion of students in positive learning environments appears to bind them to positive attitudes for learning, to a desirable acceptance of the concept of life-long learning and to demonstrate that a successful career may be developed through managing knowledge flows.

Finally, this research provides an affirmative answer to the nagging question of 'Is the considerable extra effort in pull-learning worthwhile for students, lecturers and institutions?' This research has reconfirmed the virtuous cycle of pull-learning in contrast to the push-teaching techniques widely used in core discipline subjects. This fulfils Plato's promise [31 p. 277], speaking through Socrates, of the 'utmost extent of human happiness' for the teacher arising from cultivating knowledge in those students who, brimming with potential, do respond and 'suddenly a light, as it were, is kindled in one soul by a flame that leaps to it from another, and thereafter sustains itself' [32 loc. 373].

It is not possible to generalise this affirmative answer because the application of an Empirical Bayesian methodology in this research implicitly restricts the interpretation of the results to the undergraduate and postgraduate classes that were investigated. One may nevertheless speculate on the profound implications accompanying a confirmation of the results in a wider Engineering student population.

First, the emerging 'Power of Pull' in Engineering learning highlights the importance of universities returning to their original purpose of providing outputs-based subjects that deal with knowledge flows and are underpinned by strong foundations of humanities. Alternatively, this could be embedded across all the subjects in the curriculum. These subjects constitute perhaps 10% of the existing subjects in a degree course.

In contrast, subjects that deliver core discipline declarative knowledge are distinguished by the student's need to memorise standard design methods and apply these in a variety of situations. Subjects that deliver stores of core discipline declarative knowledge to students emphasise a system of theory, imitation and practice through problem-based learning [17].

While it is difficult to compare the current understanding of knowledge with that of the ancient world, this approach to professional development is exemplified in a classic text on public speaking, *Ad Herennium* [33], which has been in continuous use for approximately 2100 years. Attributed to the great Roman philosopher, lawyer and politician Marcus Tullius Cicero (106–43 BCE), Book 1 delineates the traditional path to creativity and impressive execution through learning rules, methods and declarative knowledge (Theory), striving for effectiveness in delivery (Imitation) and assiduous Practice. In repeating this process over and over again, the student gained experience in memorising huge amounts of knowledge, became eloquent in the retrieval of this knowledge through various pattern-matching techniques and adept in the creative synthesis and analysis of the knowledge.

It is also difficult to compare the current understanding of graduate attributes with that in Cicero's day. However modern pedagogies no longer expect that memorising and diligent practice will inherently lead to the development of a student's character, individuality, independent thinking, leadership and sensibilities such as values, judgement, ethics and skills in interpersonal relationships.

The potential for differentiating push-teaching core subjects from pull-learning edge subjects is a relatively unexplored area in teaching and learning. While perhaps remaining a controversial topic among engineering educators, this dichotomy warrants further investigation as a potential source of efficiency in teaching and learning.

5. Conclusion

This research set out to answer the question of whether there are Dividend Output Factors of higher student marks for a Deep Approach to learning and the inverse of a Shallow Approach to learning in subjects designed specifically for pull-learning. Empirical data were gathered over two semesters from an undergraduate subject and a postgraduate subject. Student attitudes to the choices of Deep Leaning and Shallow Learning were assessed using Biggs' Study Process Questionnaire. These student attitudes were evaluated together with the subject performance aggregated across a number of assessment tasks.

A consistent and decisive preference was found in favour of the virtuous model of a Dividend Output Factor in higher student marks for a Deep Approach to learning and the inverse of a Shallow Approach. This is impressive across all student groups, though more reliable and demonstrable in postgraduate groups than in undergraduate groups.

The study has a number of limitations. Foremost is the reliability of Biggs' Study Process Questionnaire in the contemporary Australian university context. While this research confirmed Biggs' low level and aggregate meta factors, some uncertainties in the use of the questionnaire cannot be eliminated. For example, issues of homogeneity in and across student groups, the meaning of particular survey questions to different students, and the potential for intentional or unintentional masquerading of attitudes.

Another limitation is the small size of student classes, particularly the postgraduate classes. This necessitated the use of an Empirical Bayes approach to mine the data deeply using sensitive Bayesian inference techniques. Notwithstanding sample size limitations, a unique feature of the Bayesian perspective is that it may draw inferences from limited data although the conclusions from such research are necessarily limited to the specific groups studied and tempered by specific considerations of accuracy and reliability.

This research has validated the 'Power of Pull' in student learning in both undergraduate and postgraduate outputs-based subjects. The constructive alignment of student choices with Deep Approaches inherent in pull-learning is associated with increased subject marks in a Deep Approach Dividend Output Factor. The same is also true in the association of increased subject marks in an inverse Shallow Approach Dividend Output Factor. The finding provides confidence for the continued development of pull-learning subjects in Engineering and other disciplines.

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Appendix

Table A1. Exploratory factor analysis of Biggs' study process questionnaire responses

Analysis item[1]	Result[2]	Reliability[3]
1. Exploratory Factor Analysis of Biggs' Study Process Questionnaire (20 Questions)	Latent output factors explain 35% to 42% of the variance in responses for the two undergraduate groups, and 23% to 39% of variance for the postgraduate groups. As in Items 2 & 3 (below), these latent output factors correspond to the groups of questions mapped by Biggs to aggregate meta factors (DM+DS, SM+SS) rather than to component meta factors (DM, DS, SM, SS).	Cronbach's alpha of 0.74 to 0.86 indicates very good reliability for all groups. McDonald's Omega_h is sufficient for the first group of undergraduates and postgraduates. However, McDonald's omega is insufficient for the second groups respectively and the aggregate of all cases.

Table A1. *Continued*

Analysis item[1]	**Result**[2]	**Reliability**[3]
2. Exploratory Factor Analysis of Biggs' Study Process Questionnaire Component Meta Factors (DM, DS, SM, SS)	Biggs' component meta factors (DM, DS, SM, SS), calculated from Biggs' 20 Questions, explain 54% to 69% of variance. As in Analysis Item 1 (above) and 3 (below), aggregate (DM+DS, SM+SS) rather than component meta factors are strongly indicated.	Cronbach's alpha indicates good reliability for one postgraduate group only, and the aggregate of all cases. McDonald's Omega_h is sufficient for all groups.
3. Exploratory Factor Analysis of Biggs' Study Process Questionnaire Component Meta Factors (DM, DS, SM, SS) and Subject Mark	Underlying factors explain 55% to 59% of variance in Biggs' component meta factors & Subject Mark. As in Analysis Items 1 & 2 (above), the aggregate (DM+DS, SM+SS) rather than component meta factors are strongly indicated. In undergraduate groups, Subject Mark is uncorrelated with Deep component meta factors (DM, DS). In one postgraduate group, Subject Mark loads very weakly positively with Deep component meta factors (DM, DS) in one postgraduate group (+0.35) yet inversely with the other postgraduate group (–0.36).[6] Subject Mark is inversely correlated, albeit weakly, with Shallow component meta factors (SM, SS) in both undergraduate (–0.15 and –0.18) and both postgraduate (–0.22 and –0.32) groups.	Cronbach's alpha indicates good reliability for one postgraduate group only, and the aggregate of all cases. McDonald's Omega_h is sufficient for all groups.
4. Exploratory Factor Analysis of Biggs' Aggregate Meta Factors (DA, SA) and Subject Mark	Underlying factors explain 27% to 56% of variance. The underlying factors are volatile, sometimes comprising DA and SA distinctly, or indicating the net factor of DA-SA with or without Subject Mark. The compound factor DA-SA obscures the same analysis of Subject Mark loading with DA & SA as in Analysis Item 3 (above). Where DA & SA factors are distinct, Subject Mark loads very weakly with DA for a postgraduate group (0.32) and inversely with SA for an undergraduate group (–0.38).	Cronbach's alpha indicates poor reliability for all groups with the exception of one postgraduate group. McDonald's Omega_h is sufficient for all groups.

Notes for Table A1:

1. The Exploratory Factor Analysis was carried out with the R function 'factanal' using maximum likelihood estimation and Varimax rotation of factors [34 p. 1202]. Where 'factanal' was unable to estimate factors due to its algorithm, the R package 'psych' function 'fa' was used instead with the same estimation and rotation techniques [35 p. 74]. For example, 'factanal' is unable to calculate two factors from four variables and in this case 'fa' is used instead.
2. Factor loadings of 0.6 or greater are considered significant.
3. The number of factors was varied to ensure that the goodness of fit of the model was acceptable. Where 'factanal' was used, the p-value exceeded 0.05 such the hypothesis of perfect fit was not rejected. Where 'fa' was used, the Tucker Lewis Coefficient of Factor Reliability exceeded 0.5. The Tucker Lewis Coefficient of Factor Reliability is generally between 0 and 1, with a larger value indicating better reliability.
4. The reliability of the factor loadings was confirmed using Cronbach's Alpha and McDonald's Hierarchical Omega [35 p. 152]:
   (a) A commonly-accepted rule of thumb for Cronbach's Alpha is that 0.6–0.7 indicates acceptable reliability and 0.8 or higher indicates good reliability. Estimates for Cronbach's Alpha (and McDonald's Omega coefficient below) were prepared with the R 'psych' function 'omega' using Oblimin oblique rotation.
   (b) McDonald's Hierarchical Omega (Omega_h) coefficient of general factor saturation is the ratio of total test variance accounted for by the superordinate factor to the observed variance of the total score and values over 0.50 indicate that a measure is coherent. Only Hierarchical Omega (Omega_h) is considered, which excludes both the asymptotic value and Total Omega. Variance for the Omega_h calculation was obtained using the R Burns' 'factor.model.stat.q' package 'factor.model.stat' function [36].
5. Missing data in the survey were dealt with in two ways. Major data consistency was achieved with a relational database query selecting only complete data sets. Minor incidence of missing data in the web-based Biggs' Questionnaire responses was dealt with by substituting the middle response for the question.
6. A potentially anomalous result.

Table A2. Loading of Component Meta Factors (DM, DS, SM, SS) to Aggregate Meta Factors (DA & SA)

Analysis Item[1]	**Result**[2]	**Reliability**[3]
Item 5. Bayesian Confirmatory Factor Analysis of Biggs' Study Process Questionnaire Component Meta Factors (DM, DS, SM, SS) Note: this is the Bayesian equivalent of the Exploratory Factor Analysis Item 2 (above)	Biggs' Deep Approach (DM, DS) and Shallow Approach (SM, SS) component meta factors are all strongly loaded (0.69 to 0.87) to the respective aggregate meta factors (DA, SA). This is the case for both undergraduate and postgraduate classes, as well as for all students. Uniquenesses for all variables are satisfactorily low: DM (0.27 to 0.33, 0.24 for all), DS (0.29 to 0.35, 0.32 for all), SM (0.33 to 0.50, 0.37 for all) and SS (0.26 to 0.52, 0.28 for all).	Factors loadings pass the Heidel test for stationarity and the lengths of samples are reliable. Uniqueness loadings pass the Heidel test for stationarity, however the lengths of samples are insufficient for reliability in each of the undergraduate classes and for the total of the postgraduate classes.

Notes for Tables A2 & A3:

1. The Bayesian Confirmatory Strategy Phase models various scenarios using the R 'MCMCpack' package 'MCMCfactanal' function [37]. This function implements a Markov Chain Monte Carlo for Normal Theory Factor Analysis Model in a manner analogous to the non-Bayesian EFA 'factanal' function. MCMCfactanal simulates from the posterior distributions using standard Gibbs sampling of a normal theory factor analysis model. Normal priors are assumed for factor loadings while inverse Gamma priors are assumed for Uniquenesses. Loadings (i.e. the Lambdas) of various input variables are constrained to load exclusively on specific output factors, such that these variables do not cross-load on particular factors, and/or to positively or negatively correlate with specific output factors.
2. Reliability is assessed with the R package 'CODA' Heidelberger and Welch's convergence diagnostic 'heidel.diag' function. This function provides two reliability tests [38]:
   (a) The convergence test uses the Cramer-von Mises statistic to test the null hypothesis that the sampled values come from a stationary distribution. 'Failure' of the stationarity test indicates that a longer MCMC run is needed.
   (b) The heidel.diag diagnostic half-width test calculates a 95% confidence interval for the mean, using the portion of the chain that passed the stationarity test. 'Failure' of the half-width test indicates that the length of the sample is not long enough to estimate the mean with sufficient accuracy. However, this is in relation to the half-width assumption and is not fatal in Bayesian analysis. Such an outcome is taken into account in the accuracy of interpretation of results.

Table A3. Results of models for testing the loadings of Subject Marks to Aggregate Meta Factors (DA & SA)

Model	Results	Reliability
Model 1: Bayesian Confirmatory Factor Analysis for Biggs Aggregate Meta Factors and Subject Mark with DA Dividend Output Factor 1 (DA+, Mark–) and SA Dividend Output Factor 2 (SA–, Mark+)	Mean loadings to the DA Dividend Output Factor 1 are moderately strong with the aggregate meta factor Deep Approach having a loading of 0.45 to 0.76 (0.48 for all cases) and Subject Mark having a weaker loading of –0.32 to –0.65 (– 0.31 for all cases). Mean loadings to the SA Dividend Output Factor 2 are also moderately strong with the aggregate meta factor Shallow Approach having a loading of –0.55 to – 0.75 (–0.53 for all cases) and Subject Mark having a loading of 0.43 to 0.61 (0.50 for all cases). Uniquenesses for DA 0.42 to 0.67 (0.61 for all cases), SA 0.36 to 0.61 (0.61 for all cases) and Mark 0.32 to 0.50 (0.43 for all cases) are moderate.	Undergraduate groups pass Heidel stationarity test but fail sample size test. Postgraduate groups pass both Heidel stationarity test and sample size test.
Model 2: Bayesian Confirmatory Factor Analysis for Biggs Aggregate Meta Factors and Subject Mark with DA Dividend Output Factor 1 (DA+, Mark+) and SA Dividend Output Factor 2 (SA–, Mark+)	Mean loadings to the DA Dividend Output Factor 1 are not strong with the aggregate meta factor Deep Approach having a loading of 0.46 to 0.70 (0.43 for all cases) and Subject Mark having a loading of 0.29 to 0.53 (0.30 for all cases). Mean loadings to the SA Dividend Output Factor 2 are moderately strong with the aggregate meta factor Shallow Approach having a loading of –0.57 to –0.65 (–0.65 for all cases) and Subject Mark having a loading of 0.39 to 0.53 (0.37 for all cases). Uniquenesses for DA 0.49 to 0.63 (0.66 for all cases), SA 0.48 to 0.56 (0.46 for all cases) and Mark 0.39 to 0.52 (0.55 for all cases) are moderately satisfactory only for Mark.	Undergraduate groups pass Heidel stationarity test but fail sample size test. Postgraduate groups pass both Heidel stationarity test and sample size test.
Model 3: Bayesian Confirmatory Factor Analysis for Biggs Aggregate Meta Factors and Subject Mark with DA Dividend Output Factor 1 (DA+, Subject Mark correlation excluded) and SA Dividend Output Factor 2 (SA–, Mark+)	Mean loadings to the DA Dividend Output Factor 1 are very strong with the aggregate meta factor Deep Approach having a loading of 0.84 to 0.86 (0.84 for all cases) while Subject Mark was excluded from cross-correlating to Factor 1. Mean loadings to the SA Dividend Output Factor 2 are only moderate with the aggregate meta factor Shallow Approach having a loading of –0.49 to –0.63 (–0.45 for all cases) and Subject Mark having a loading of 0.50 to 0.63 (0.59 for all cases). Uniquenesses for DA 0.22 to 0.26 (0.23 for all cases), SA 0.58 to 0.65 (0.68 for all cases) and Mark 0.57 to 0.61 (0.52 for all cases) are satisfactory only for DA.	Undergraduate groups pass Heidel stationarity test but fail sample size test. Postgraduate groups pass both Heidel stationarity test and sample size test.

Table A4. Comparison of models using Bayes Marginal Likelihoods and Bayes Factor Ratios

Bayes Log Marginal Likelihoods[1,3]	**ug1**	**ug2**	**Total ug**	**pg1**	**pg2**	**Total pg**	**All Cases**	**Model Preference[2]**
Model 1	–1010	–1006	–1980	–152	–156	–290	–2253	
Model 2	–817	–903	–1472	–125	–143	–258	–1839	
Model 3	–967	–996	–1953	–149	–155	–285	–2169	
Bayes Factor Ratios								
Model 2 / Model 1	193	103	508	27	13	31	414	All decisive
Model 2 / Model 3	150	94	482	24	12	27	330	All decisive
Model 3 / Model 1	43	9.6	26				84	Decisive
				3.4		4.6		Strong
					0.6			Negative

Notes for Table A4:
1. Model comparison is carried out with the R 'MCMCpack' package 'MCMCregress' with Chib marginal likelihood [39] and 'BayesFactor' functions [37]. All results are expressed as natural logarithms.
2. Model Preference is a qualitative scale for the notional strength of evidence [25].
3. Models 1, 2 & 3 embody an inverse Shallow Approach (SA) related Dividend Output Factor in concert with three variants of a Deep Approach (DA) related Dividend Output Factor. In addition, the three variants were evaluated with a non-inverse Shallow Approach (SA) related Dividend Output Factor (i.e. a positive loading of Subject Mark with a Shallow Approach to learning). As expected from the Exploratory Factor Analysis phase, the non-inverse Shallow Approach models are significantly inferior to Models 1 to 3.

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