Sustainable Growth for 'Robert': Constructive Alignment and Student Activity in Enterprise Education

Vic Curtis, Course Director, BLSS, University of Derby

Introduction

Student participation in higher education has increased dramatically in recent years. In the UK for example, undergraduate student numbers have increased 47% from 1.39m to 2.04m in the 25 years from 1996/97 to 2021/22 (HESA, 2023). This has resulted in a student population with far greater diversity of commitment, abilities and skills, which presents many challenges for teaching, including for enterprise and entrepreneurship education [EEE] (Macht and Ball, 2016; Scott et al, 2020). Biggs and Tang (2011) classify this difficulty as the 'Robert and Susan problem' which they illustrate with two hypothetical students: 'Academic' Susan who is "academically committed, and will learn well, virtually whatever the teaching" (p.3) and 'Non-academic' Robert who is "at university simply to obtain a good job, he is not academically inclined, and he represents the student who would not have been at university years ago" (p.3). With the proportion of Roberts in the classroom increasing, Biggs and Tang's (2011) concern is that such students are "not responding to the methods that work for Susan" (p.5) and that they need more help to succeed.

Biggs and Tang (2011) contend that Susan engages meaningfully using the appropriate cognitive level, develops her knowledge and skills, relates these to her prior learning considering the larger picture and constructs new meaning for herself. She automatically adopts a deep approach to learning (Marton and Saljo, 1976a; 1976b; Svensson, 1976). Within EEE, her entrepreneurship-related human capital is growing (Martin et al, 2013). Robert, on the other hand, adopts a surface approach to learning in that he engages only minimally, uses rote learning, memorises and reproduces unrelated facts, and tries to get by with minimum effort. He is using lower order cognitive levels irrespective of the task and his entrepreneurship-related human capital is not growing to its full potential.

Constructive alignment is suggested as an approach to overcome this 'Robert and Susan problem' (Biggs, 1993; 1999; Biggs and Tang, 2011). It encourages students to actively enact the learning outcomes of their courses through engaging with the appropriately aligned tasks, activities and assessments which the teacher has designed, and in so doing, allows students to construct their own knowledge and meaning (Biggs and Tang, 2011). This principle has become central to higher education quality processes and curricula (QAA, 2018a) and is embedded in best practice EEE guidance (QAA, 2018b; Sear and Norton, 2021).

To exemplify the impact of constructive alignment, Biggs and Tang (2011) present a hypothetical graph which shows proposed relationships for both Susan and Robert between increasingly complex levels of cognitive engagement which represent enhanced deep learning and increasing levels of student activity. This graph is shown in Figure 1.

> Please note that due to copyright restictions, Figure 1 has been removed and cannot be shown. It is available on p.6 in Biggs J. and Tang C. (2011) *Teaching for Quality Learning at University*, 4th Ed., Maidenhead: Open University Press

Figure 1: Student orientation, teaching method and level of engagement
[Source: Biggs and Tang (2011)]

The graph suggests Susan can cope with passive learning environments (e.g. a standard lecture) as she adopts a deep approach to learning and works at a high cognitive level spontaneously. Robert, however, struggles in such passive conditions, uses sub-optimal cognitive approaches and therefore engages in surface learning. This leads to engagement gap 'A' at the passive end of the continuum. Biggs and Tang (2011) contend that as the level of student activity increases within constructively aligned curricula, Susan will become progressively deeper in her approach to learning. The constructively aligned curricula requires that Robert use more appropriate, higher order cognitive levels to actively enact the learning outcomes and he will therefore progress from surface towards deep learning. Importantly, Biggs and Tang hypothesize that Robert will gain proportionately more than Susan with such increasing activity which results in reduced engagement gap 'B' at the active end of the continuum. Robert will therefore be more able to fulfill his potential through sustainable learning growth. However, equally importantly, Biggs and Tang (2011) do not present any empirical quantitative evidence to substantiate these hypotheses, neither within EEE nor across the wider HE sector. This is important as if it can be demonstrated that this approach has a greater impact on Robert than Susan, this could encourage increased use of active constructive alignment within EEE which would help create sustained learning and entrepreneurship-related human capital growth in the 'unexpected place' of Robert who represents the rising proportion of such students in today's classrooms.

Literature Review

The work of Biggs and colleagues (1999; 2011; 2012) builds on the deep and surface approaches to learning studies of Marton and Saljo (1976a, 1976b). Biggs describes the characteristics of surface learning as an intention to reproduce content through minimal engagement whereas deep learning is intending to understand through appropriate engagement and relating new to existing knowledge to create one's own meaning through a constructivist approach (Biggs and Tang, 2011). However, the context within which the students learn partially determines whether they will take a deep or surface approach to their learning and it is not wholly some innate student attribute or characteristic (Biggs and Tang, 2011). For example, Ramsden (2003) describes approaches to learning as "responses to the educational environment in which students learn" (p.53) whilst Entwistle (1991) goes further stating "it is the students' perceptions of the learning environment that influence how a student learns and not necessarily the context itself" (p.202). This is demonstrated in the 3P model of student learning (Biggs, 1993; Biggs, 1999; Biggs et al, 2001) which is shown in Figure 2.

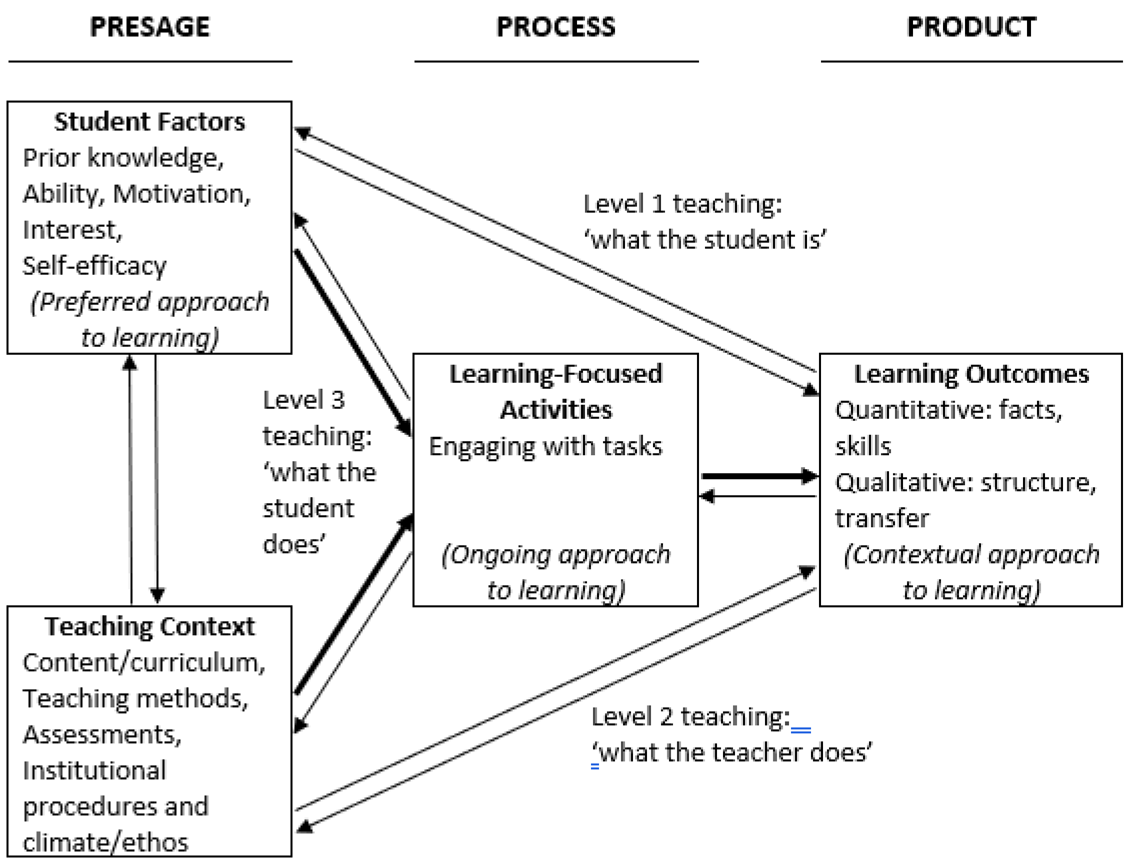

Figure 2: 3P Model of Student Learning
[Source: Developed by the Author from Biggs (1993), Biggs (1999) and Biggs et al, (2001)]

Biggs conceptualises student learning as being a system of presage factors (student factors and the teaching context), process factors (the learning activities and tasks) and product factors (the outcomes of the learning). Student factors are those such as prior knowledge, ability, motivation, interest in the topic and degree of self-efficacy, whereas the teaching context are factors including the content and curriculum which is being taught, the manner of the teaching and how that is assessed, the climate within the classroom and institution, and the wider institutional procedures which must be operated within. The process factors are the activities and tasks which the students engage with during learning whilst the outcomes can be quantitative such as facts or skills learnt, or can be qualitative such as being able to determine overall structures and transfer that to other situations (Biggs, 1993; Biggs, 1999; Biggs et al, 2001). This is the theoretical framework which Biggs uses to underpin his view of deep and surface approaches to learning.

Biggs (1999) also conceptualises three levels of teaching. Level 1 has a focus on "what the student is" (Biggs, 1999, p.21) and this accentuates the student factors and characteristics as the reason why some may not do well, and that it is nothing to do with the teaching. It is a deficit model which suggests that the student may be lacking some attribute to explain why they don't learn, which Biggs and Tang characterise as a "*blame-the-student* theory of teaching" (2011, p.18). The counterpoint is Level 2 teaching which has a focus on "what the teacher does" (Biggs, 1999, p.22). In this scenario, "learning is seen more as a function of what the teacher is doing than of what sort of student one has to deal with" (Biggs, 1999, p.22). Biggs still considers this a deficit model, although the blame now lies with the teacher if the students do not learn.

However, for Biggs, the preferred progression of learning is given by the heavy arrows in Figure 2. and this represents Level 3 teaching. This has a focus on "what the student does, on what learning is or is not going on" (Biggs, 1999, p.24) and starts with the interaction of the student factors and teaching context, develops through the learning-focused activities and finishes with the outcomes of the learning. This level of teaching is about supporting student learning and depends on both students factors and the teaching context. Biggs et al (2001) suggest that students will have their preferred approaches to learning based on the student factors, but that the actual ongoing approach to learning students adopt during the learning activities will depend on and be influenced by the interaction with and their perception of the teaching context. This aligns with the views of Ramsden (2003) and Entwistle (1991). The contextual approach to learning will then be the overall approach adopted by the students in achieving the learning outcomes and again will be influenced by student factors, teaching context and learning activities.

The reduction in the engagement gap between Susan and Robert in Figure 1. is explained through the 3P model in that the interaction between the student factors and teaching context determines the approach to learning during the learning-focused activities and hence the quality of the learning outcomes (Biggs, 1999). When the teaching context is passive, student factors are more dominant in determining the ongoing approach to learning. Those students such as Susan who have greater ability, prior knowledge and interest will be able to cope with this and will likely adopt a preferred deep approach. However, those students such as Robert will struggle more as the passive teaching context does not help them to take a deep learning approach and they are more likely to adopt their preferred surface approach. As the teaching context becomes more active through constructive alignment, the balance of the system changes and context begins to have more influence on the cognitive levels which the students use. The greater activity from the teaching context helps Susan to enhance her deep approach a little, but has a significantly larger effect on Robert to help him move from a surface towards a deeper approach through encouraging him to use higher cognitive levels in the learning tasks. Thus, the concept of constructive alignment (Biggs and Tang, 2011) is partially premised on hypothetical students Robert and Susan, and how they respond to differing levels of activity elicited by the tasks they are set and the approach to learning they take during those tasks.

The hypothetical graph suggests that level of student activity for both hypothetical students is associated with and could be used to predict deep approaches to learning. This is further implied by Biggs' claim of a "two-way interaction" (2012, p.40) and his assertion that increased activity "*requires* Robert … to use the higher order cognitive activities that Susan uses spontaneously" [italics in original] (2012, p.41). Therefore, he anticipates that increasing the level of student activity through constructively aligned teaching and learning activities relates to increasing levels of student cognitive engagement and deeper learning, but more so for Robert than Susan. He implies a causal relationship, though does not explicitly state that. What is less clear, however, is the evidence basis for the shape of the hypothetical graph. Biggs is quite vague on the underpinning evidence for these claims, saying only they were based on "a number of studies and observations summarized in Biggs (1999)" (Biggs, 2012, p.40), although he does not specify which studies or observations, nor what their contributions are. If the graph is not accurately representing the association between level of activity and deeper approaches to learning, there appears to be little empirical evidence that employing this approach will further enhance the deep learning of the Roberts compared to the Susans.

Numerous meta-analyses demonstrate that active, experiential learning produces better academic outcomes than passive learning (Bligh, 1998; Burch et al, 2019; Freeman et al, 2014; Kozanitis and Nenciovici, 2022). However, these analyses are across whole cohorts of students and do not consider Susan or Robert separately. In fact, given the ubiquity of constructive alignment within HE, there is surprisingly little discussion of Bigg's hypothetical students within the literature. Several studies discuss the 'Robert and Susan problem' (e.g. Asting and Swanberg, 2011; Boyd, 2015; Lewis and Harrap, 2008; Wickramasekera et al, 2009), but only in describing more active learning being associated with deeper learning and constructive alignment, and in relation to the increased diversity of students in the classroom. None of these studies provide any empirical evidence to support the different approaches that the two students are suggested to take, nor of the shape of the hypothetical graph, as proposed by Biggs and Tang (2011), nor even how one might differentiate between the two types of students in a consistent way.

The only study to offer empirical evidence and which refers obliquely to 'Robert' and 'Susan' is by Balasooriya et al (2009) who investigate the adoption of more active teaching pedagogies within three medical settings. Balasooriya et al (2009) simplify Biggs' (1999) original 'hypothetical graph' to change from a continuum over a range of passive to active contexts to only consider the end points of a linear graph drawn between an initial passive context and a later active context. The pre and post measurements provide the end points for these linear graphs, although no substantiation or discussion is given as to why this graphical approach is used. However, Balasooriya et al (2009) find that one small sub-group of students act as 'Susans' and increase from deep approaches in the passive teaching to even deeper during the active teaching, whilst another small sub-group act as 'Roberts' and increase from less deep to more deep. The 'Roberts' gain at a greater rate than the 'Susans' but do not reach the same levels of deep learning as 'Susan'. No analysis of association nor rate of change of deep learning to determine if the 'Susans' and 'Roberts' are significantly different is presented.

A second issue with the active learning meta-analyses is that none include studies from EEE despite there being a 'taken for granted' assumption within the discipline that an active, experiential and constructivist approach to student learning is the preferred way to teach the subject (Curtis et al, 2021). This is presented as best practice (QAA, 2018b; Sear and Norton, 2021), and the idea is extensively supported by the EEE literature (Jones et al., 2019; Lackeus, 2016; Martin et al., 2013; Morris and Liguori, 2016; Nabi et al., 2017; Neck and Corbett, 2018). However, despite this assertion, the evidence that this active learning is practised across the sector is mixed. Several EEE reviews have demonstrated more traditional and more passive approaches in operation (Bae et al, 2014; Pittaway and Cope, 2007; Pittaway and Edwards, 2012; Rideout and Gray, 2013) whilst others suggest that EEE pedagogy literature has moved from "teacher-guided instructional models to more constructivist perspectives… [from]… the issue of teachability to a greater emphasis on learnability" (Hagg and Gabrielsson, 2020, p.829). These diverse views indicate that there is variability in the level of student activity enacted within EEE.

Furthermore, although the literature claims that EEE uses an active, experiential pedagogy as best practice (Martin et al, 2013; Nabi et al, 2017; Neck and Greene, 2018), the evidence of the impact of this approach is often limited to "short term and highly subjective impact measures" (Hagg and Gabrielsson, 2020, p.832) such as entrepreneurial intention. Evidence of longer term softer impacts such as development of student learning or harder impacts such as number of businesses started are also limited (Bozward et al, 2022; Nabi et al, 2017), although it has been proposed that measures of impact from the wider education literature could be used (Blenker et al, 2014; van Ewijk, 2018) and deep learning could be one of these measures (Curtis et al, 2021; Moon et al, 2013). This would be especially valuable for the two hypothetical students Robert and Susan to determine if different approaches to learning are adopted within a range of more passive to more active EEE teaching.

Relatively few studies have investigated active classroom settings within EEE to determine whether deep learning was promoted, and even fewer have demonstrated any correlation or regression relationships. Indeed, Scott et al (2016) refer to the lack of evidence on the impact of active and experiential EEE as "the paucity of 'evaluations of effectiveness'" (p.83). The work of Curtis and colleagues (2013; 2021; 2021a; 2022) provides the most detailed analysis of the association of deep approaches to learning and levels of student activity within EEE. These studies were undertaken through applying the validated Revised 2-Factor Study Process Questionnaire [R-SPQ-2F] (Biggs et al, 2001) across a variety of undergraduate modules from first year (level 4) to final year (level 6). For example, Moon et al (2013) demonstrate significantly more deep learning during a more active case study pedagogic approach than a more traditional lecture style approach for first year business students. More active pedagogic approaches involving discursive case studies, live briefs and video assessments were more effective for promoting deep learning whereas prepared Powerpoint slides had little impact.

Curtis et al (2021) investigated one constructively aligned final year undergraduate EEE module over a period of six years ($n = 173$) to determine the association between deep approaches to learning, and level of student activity. The study demonstrated Spearman correlations between deep learning and level of student activity at the end of the module of 0.310 ($p < 0.001$). Student quotes suggested the use of live briefs for real companies and innovative video assessments seemed to assist in developing student interest which corroborates Moon et al (2013). It is worth noting however that re-analysis of the data suggests no non-normality was present in the data and so a linear model is reasonable and appropriate for all students. This also aligns with the linear graphs produced by Balasooriya et al (2009).

So, returning to Biggs and Tang's (2011) hypothetical graph, the curve functions for Susan and Robert may be simplified by considering linear relationships between level of student activity elicited and level of engagement. This is shown in Figure 3 which also demonstrates increasingly deep learning being achieved with higher levels of complexity and cognitive engagement.

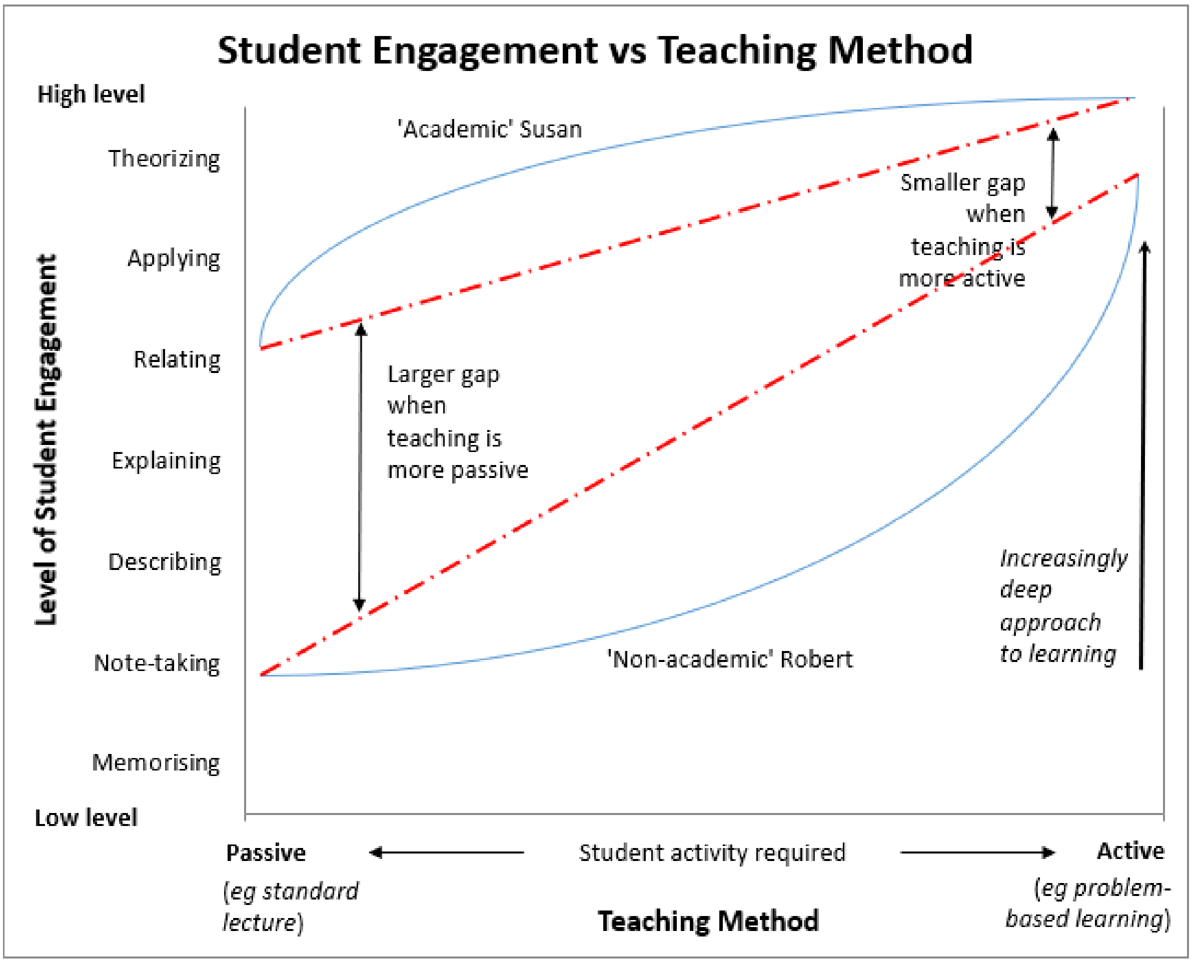

Figure 3: Student engagement vs teaching method
[Source: Developed by the Author from Balasooriya et al (2009), Biggs and Tang (2011) and Biggs (2012)]

These linear relationships are shown increasing across the full continuum from the passive end of each original curve to the active end. This is a development of Balasooriya et al (2009) who only considered the two end points and no points in-between. Extending the linear approach to Susan and Robert also allows correlation and regression analysis to be undertaken (Pallant, 2016) and any significant differences between Susan and Robert to be established. Additionally, linear models are more widely understood than curvilinear models (Field, 2018) and such examples are therefore more likely to be acted upon by practitioners (Black and Wiliam, 1998).

Figure 3 shows that increasingly deep learning (as signified by level of engagement) is associated with a change in level of student activity from passive towards active as suggested by constructive alignment. However, there are differing linear relationships for Susan and Robert. The relationship for Susan is shown as being above that of Robert although the relationship for Robert is steeper than that of Susan. This simplified version of Biggs and Tang's (2011) hypothetical was tested within the present study. Using deep learning as a measure of impact within constructively aligned EEE curricula, the aim of the study was to establish if the 'Robert and Susan problem' (Biggs and Tang, 2011) was evident within EEE, to investigate whether Robert's deep learning grew more rapidly than Susan's with increasing level of student activity and to determine the degree to which deep learning is predicted by level of student activity for each hypothetical student.

Methodology

Using two constructively aligned EEE modules at a post-92 University in the UK, the study measured the levels of deep learning and student activity at the beginning, middle and end of teaching over one semester. These time-based contexts were based on the 3P model of student learning (Biggs, 1993, 1999) which proposes presage, process and product factors to account for the approach to learning which students adopt and should be measured using an instrument which aligns with the underlying student approach to learning theory (Asikainen and Gijbels, 2017). Consequently, deep learning was measured using the validated revised two-factor Study Process Questionnaire [R-SPQ-2F] (Biggs et al, 2001) whilst level of student activity was measured using the same 7-point scale of passive to active learning in EEE as Curtis et al (2021), although the latter was transformed through a square root transformation and standardized to reduce non-normality to within acceptable limits (Tabachnick and Fidell, 2013) Students were asked to complete the questionnaire about their own most liked previous module at the start of the semester (Q_1, n = 107) and then about the EEE module they were studying, both at the middle (Q_2, n = 106) and end (Q_3, n = 92) of the semester. The most liked module was used as an initial baseline to provide a consistent point of comparison. Previous work suggests this to be at the top of the range of deep learning over which students tend to operate and equates to their preferred approach to learning in that context (Kember et al, 2008).

To establish a repeatable procedure to align student data from the questionnaire to either Susan or Robert, pre-specified comparators were adopted (Gorard, 2013). These were again based on the 3P model of student learning and involved taking one factor from each of the presage, process and product categories, ranking all the students on that factor and then splitting the cohort about the median value. If the student was above the median for two or three of the factors, that student data was aligned to Susan whereas if above the median for one or none of the factors, the student data was aligned to Robert. The presage factor chosen was the mean grade achieved for the previous semester's modules as an indicator of ability (Duff, 2004); the process factor was the attendance in class as an indicator of engagement (Crede et al, 2010); the product factor was the EEE module grade as an indicator of achievement of the learning outcomes (Biggs and Tang, 2011). Although the comparators were pre-specified, it was not known during teaching which students' data would be allocated to Susan or Robert as that could not be established until after the modules were completed and marked. Therefore, the students were not aware of how data was allocated and no differential in the teaching could be applied to either group. Both the questionnaire and the Susan / Robert allocation procedure were approved by the appropriate Research Ethics Committee as part of the author's Doctoral programme.

Results

There were 153 students registered on the two EEE modules under investigation (32% female, Mean age = 21.04 years, SD = 4.35 years). Using the presage, process and product criteria given, the number of students aligning with Susan and Robert within the sampling population of both module cohorts, the numbers of female students within the sampling population and the numbers of respondents who answered the various questionnaire iterations were determined. These are given in Table 1.

	Susans	**Roberts**	**Total**	**t or χ^2 Stat**	**p**
Number in sampling population	75	78	153	-	-
Mean Age	21.38	20.71		0.95	0.342
SD Age	5.08	3.51		-	-
Number of females from sampling pop'n	34	15	49	11.97	<0.001
Number of valid Q_1 respondents	68	39	107	30.07	<0.001
Number of valid Q_2 respondents	66	40	106	24.22	<0.001
Number of valid Q_3 respondents	61	31	92	27.59	<0.001

Table 1: Numbers of 'Susans' and 'Roberts' in Sample Modules

The mean age of the students aligned to Susan (21.38 years) and Robert (20.71 years) were not significantly different ($t = 0.95$, $df = 151$, $p = 0.32$). However, more female students were aligned to Susan than to Robert and more male students aligned to Robert. 34 out of the 49 female students (69%) were aligned to Susan whilst 63 out of the 104 male students (61%) were aligned to Robert. These differences were significant ($\chi^2 = 11.97$, $df = 1$, $p < 0.001$), so the choice of female and male hypothetical students by Biggs and Tang (2011) would not seem unreasonable.

Given the characteristics of Susan compared to Robert (Biggs and Tang, 2011), it might be expected that those students more aligning with Susan would be more conscientious and therefore more likely to answer questionnaires than those aligning with the Robert. This hypothesis is strongly upheld with all three questionnaires being completed by significantly more Susans than Roberts ($p < 0.001$). Hence, the allocation of student data to align with either the hypothetical Susan or Robert would seem to be reasonable. These results demonstrate that the allocation of student data between Susan and Robert was both reasonable and repeatable, that more females were allocated to Susan and more males to Robert and that there were significant differences between the numbers of Susans and Roberts completing the questionnaires. This is the first contribution of this study.

Analyses were undertaken of the association between deep learning and level of student activity results for Susan and Robert, but then Susan was also compared to Robert to determine if there were differences between the two hypothetical students. Figure 4 shows the graphs of the linear regression models between deep learning and level of student activity for most liked, mid EEE module and end of EEE module results for both Susan and Robert whilst Table 2 gives the regression model and its coefficients.

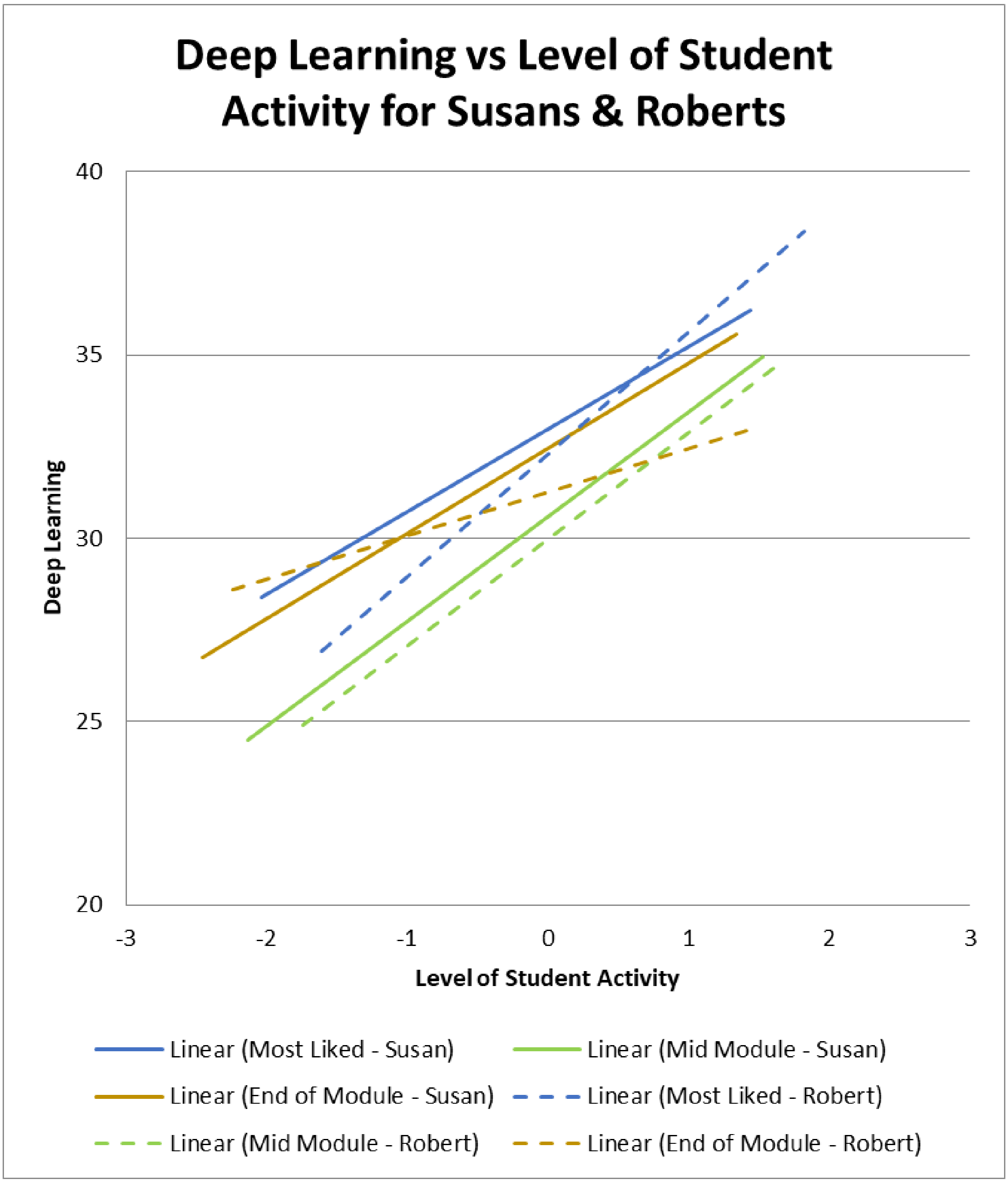

Figure 4: Linear Regressions between Deep Learning and Level of Student Activity for Susan and Robert

Module	N	R^2	F	p	Deep Learning Model	Unstandardized Coefficient			β	95% Confidence Intervals [Lower, Upper]
						B	SE	p		
Susan										
Most Liked	68	0.098	7.187	0.009	Constant	32.985	0.833	< 0.001		31.322, 34.648
					LSA	2.250	0.839	0.009	0.313	0.574, 3.925
Mid Module	66	0.177	13.777	< 0.001	Constant	30.591	0.764	< 0.001		29.065, 32.177
					LSA	2.857	0.770	< 0.001	0.421	1.319, 4.395
End of Module	61	0.096	6.301	0.015	Constant	32.475	0.920	< 0.001		30.635, 34.316
					LSA	2.328	0.928	0.015	0.311	0.472, 4.185
Robert										
Most Liked	39	0.252	12.487	0.001	Constant	32.308	0.934	< 0.001		30.415, 34.201
					LSA	3.344	0.946	0.001	0.502	1.427, 5.262
Mid Module	40	0.156	7.019	0.012	Constant	29.975	1.083	< 0.001		27.672, 32.168
					LSA	2.906	1.097	0.012	0.395	0.686, 5.127
End of Module	31	0.031	0.917	0.346	Constant	31.258	1.224	< 0.001		28.754, 33.762
					LSA	1.192	1.244	0.346	0.175	-1.354, 3.737

Table 2: Linear Regressions of Level of Student Activity with Deep Learning for Susan and Robert

For Susan, there were significant positive associations between deep learning and level of student activity for most liked module ($p = 0.009$), mid EEE module ($p < 0.001$) and end of EEE module ($p = 0.015$), with correlation coefficients ranging from 0.311 – 0.421. For Robert however, only most liked ($p = 0.001$) and mid EEE module ($p = 0.012$) contexts provided significant positive associations with correlations ranging from 0.395 – 0.502. The end of EEE module correlation for Robert ($R = 0.175$, $p = 0.346$) was not significant. Nonetheless, these results are all positive in direction and provide strong support for the linear model line for Susan and reasonable support for linear model line for Robert in Biggs and Tang's (2011) simplified linear hypothetical graph under a variety of different contexts.

Table 2 also shows that for Susan, the 95% confidence intervals on the three unstandardized gradients were not significantly different from each other (e.g. if the true value of the gradient was 3, this would be contained within all 95% confidence intervals). This again provides strong evidence that the linear model line applies to Susan for deep learning in a variety of circumstances. Similarly, for the two significant deep learning regressions for Robert, the 95% confidence intervals on unstandardized gradients were not significantly different from each other (e.g. if the true value of the gradient was 4, this would be contained within those 95% confidence intervals). This also provides reasonable evidence that the linear model line applies to Robert for deep learning in a variety of circumstances, those less than for Susan.

Although the unstandardized gradient of Robert would appear to be steeper than that for Susan in the most liked and mid EEE module contexts, the range of 95% confidence intervals applying to Susan and Robert also overlap (e.g. if the true value of the gradient was 3.5, this would be contained within all 95% confidence intervals). Therefore, the gradients of Susan and Robert are not, in themselves, significantly different. This is not in keeping with the Biggs and Tang (2011) hypothetical graph which suggests that Robert increases his deep learning at a greater rate than Susan and would thus have a significantly steeper gradient in the regression line. Therefore, the hypothetical graph is only partially supported on this point.

Table 2 also shows the 95% confidence intervals around the regression y-intercept constant values (i.e. where standardized level of student activity is 0) for the most liked, mid EEE and end of EEE modules for both Susan and Robert. All of these constants also overlap (e.g. if the true value of the constant was 32, this would be contained within all 95% confidence intervals). This demonstrates there is no significant difference in deep learning between Susan and Robert at this point in any of the contexts and therefore Susan is not necessarily always above Robert in terms of deep learning, as suggested by Biggs and Tang (2011).

Significant positive relationships between deep learning and level of student activity have previously been demonstrated in earlier studies within EEE by Curtis and colleagues (2021; 2021a; 2021b; 2022). Although these were all whole cohort studies and therefore did not align data to either Susan or Robert, they do support the size, direction and significance of the relationships between deep learning and level of student activity within the present study. These results also align with Lackeus (2016) in that both modules considered had elements of creating value for others as part of their constructively aligned curricula which resulted from the students 'doing something' and being active and experiential in their learning. Best practice within EEE also suggests an active approach is preferred (Nabi et al, 2017; QAA, 2018b; Sear and Norton, 2021) and these results support that approach.

The evidence of the positive linear model lines suggests two principal implications, one for theory and one for practice. The results suggest that increased levels of student activity are strongly associated with increased deep learning for both Susan and Robert. This supports Biggs and Tang's (2011) principal hypothesis that greater student activity through constructively aligned curricula is associated with deeper learning and this can aid Robert to learn more in the manner of Susan. Furthermore, as Biggs and Tang's (2011) hypothetical graph suggests, Robert appears to gain at a faster rate than Susan with increased activity in two of the three contexts. However, this increased rate of deep learning of Robert above Susan is not significant and therefore Robert can only be said to be gaining at the same rate as Susan, although this 'unexpected growth' is still beneficial.

Similarly, the level of deep learning achieved by Susan and Robert at different points during the module does not appear to be significantly different as the mid EEE and end of EEE modules were not significantly different from the students' most liked module. This suggests that the current constructively aligned and active EEE teaching approach helps promote similarly high levels of deep learning for both Susan and Robert.

Hence, from a theoretical perspective, the simplified linear Biggs and Tang's (2011) hypothetical graph is only partially supported. This means that the constructive alignment arguments that Robert always gains more than Susan, and that Susan is always at a higher level of deep learning than Robert are perhaps not as robust as first thought. However, the implication for EEE practice continues to be that constructively aligned activity should be incorporated within teaching as Robert does still gain, and potentially gains at a faster rate than Susan. However, even if Robert only gains at the same rate as Susan, it is still worthwhile in terms of increased deep learning.

Implications for Policy and Practice

This study has demonstrated that constructively aligned EEE curricula in which students actively enact the learning outcomes promotes growth in deep learning. This provides additional evidence for policymakers that constructive alignment, as suggested by QAA and EEE guidelines (2018a; 2018b) should be encouraged. In terms of implications for practice, teachers should ensure that curricula are constructively aligned and that students are active in their learning. This should particularly help the increasing numbers of Roberts in today's classrooms who can sustain their 'unexpected growth' in deep learning from this enhanced activity to gain at least as much as the Susans, and possibly more so.

ORCID iD: Vic Curtis https://orcid.org/0000-0002-5800-6697

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