Approaches to Measuring Attendance and Engagement

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Abstract

In this paper, we argue that, where we measure student attendance, this creates an extrinsic motivator in the form of a reward for (apparent) engagement and can thus lead to undesirable behaviour and outcomes. We go on to consider a number of other mechanisms to assess or encourage student engagement – such as interactions with a learning environment – and whether these are more benign in their impact on student behaviour i.e. they encourage the desired impact as they are not considered threatening, unlike the penalties associated with non-attendance. We consider a case study in Computer Science to investigate student behaviour, assessing different metrics for student engagement, such as the use of source control commits and how this measure of engagement differs from attendance.

Introduction

In this paper, we consider different data sources that may be used to indicate engagement, and how these forms of indicators may themselves alter student behaviours in unintended ways.

Student engagement is recognised as important for higher education (Fitzgerald et al, 2016), leading to initiatives such as the UK Engagement survey (Higher Education Academy, 2018). However, defining and measuring engagement is problematic (Zebke, 2014); attendance data is sometimes used as a proxy for engagement, but raises the question of whether attendance is indeed a suitable predictor for student performance, and whether it has other effects on student behaviour (Guardian, 2018) In this paper, we address the question: “do students actively engage with the attendance monitoring system without actually engaging in the work”? We go on to suggest alternative metrics for engagement.

To enable us to measure engagement, we consider interaction with a source control system (a key tool in programming), as well as engagement indicators from interactions with learning materials and assessments. Through reviewing the use of these alternative indicators for engagement, we are able to address a related issue, namely “are indicators that are not linked with any extrinsic motivators better for measuring student engagement?”

Engagement

Student engagement is considered as increasingly important for higher education (Fitgerald et al, 2016), with growing concerns about student retention rates and academic success (Woodfield, 2014). However, measuring and assessing engagement is a challenge, with the fundamental questions being what is engagement and how do we measure it? Furthermore, some potential measures, – such as the use of student attendance as a proxy for engagement – may create an extrinsic motivator and in itself lead to undesirable behaviours for those responding to it, as well as undesired outcomes for their peers whose learning environment and experience is adversely affected (Gneezy et al, 2011).

As described above, student engagement is recognised as important for higher education, leading to initiatives such as the UK Engagement survey. As noted by Zepke (2014), such surveys – in the UK and elsewhere – seem to focus on a technical interpretation, which is considered to be measurable. However, defining and measuring engagement is problematical; attendance data is sometimes used as a proxy for engagement as, whilst non-trivial to collect *en masse* and reliably, it is still relatively easy to collect, is easily measurable and can thus be reported and acted upon.

The challenge posed by measures such as attendance, is that the measure itself may alter behaviour, but in unintended ways. In the next section we consider the concept of motivation and then go on to explore alternate ways to measure engagement, in the context of computer science teaching.

In general tertiary education, some form of virtual learning environment is typically used to either provide the main platform for learning, or to supplement more traditional face-to-face teaching. Such learning systems – and other online tools offer new data on what students are doing, and can enable us to carry out Learning Analytics. This utilises tools and techniques from the world of Big Data, with educational data mining considering how we can collate and use of large sets of data on student learning.

Motivation

Motivation in the context of university students is concerned with encouraging them to act in a way that the teachers intend, the key aim being to encourage the students to achieve the learning outcomes, developing the skills and knowledge that the module, course or degree are intended to develop. Motivation may be fostered through the design of suitable activities and assessment mechanisms, and such motivating factors can be characterised as extrinsic or intrinsic (Ryan & Deci, 2000).

Extrinsic Motivator: this is something that encourages behaviour through rewards such as money, grades, credits etc.

Intrinsic Motivator: something that encourages behaviour through the sense of being worthwhile to the individual, i.e. internal rewards.

Extrinsic and intrinsic motivators may conflict; incentives designed to encourage extrinsic motivation may, on the contrary, decrease intrinsic motivation (Hanus & Fox, 2015).

Where we measure student attendance, this can create an extrinsic motivator in the form of a reward for engagement and can lead to undesirable behaviour or effects (Visaria at al, 2016), although Nowell (2017) argues that motivation, whether extrinsic or intrinsic, leads to more satisfied students than those who lack either form of motivation.

Measuring Engagement in a Computer Science degree

The data and figures in this paper relate to experience of the authors within the teaching of computer science, though much is applicable to other science and non-science disciplines.

In the context of a number of core computing modules, we consider attendance, and the impact of attendance monitoring, and how far attendance can be a predictor of performance. We also consider more general interaction with a learning environment, partly encouraged through the use of a range of tailored assessment approaches.

Whilst the above two indicators are considered within the context of a Computer Science case study, they can be applied to other disciplines. As a final indicator, we consider interaction with source control (a key tool in programming).

This set of engagement indicators – from attendance, interactions with learning materials and assessments on a virtual learning environment, and source control – provide a range of indicators for engagement

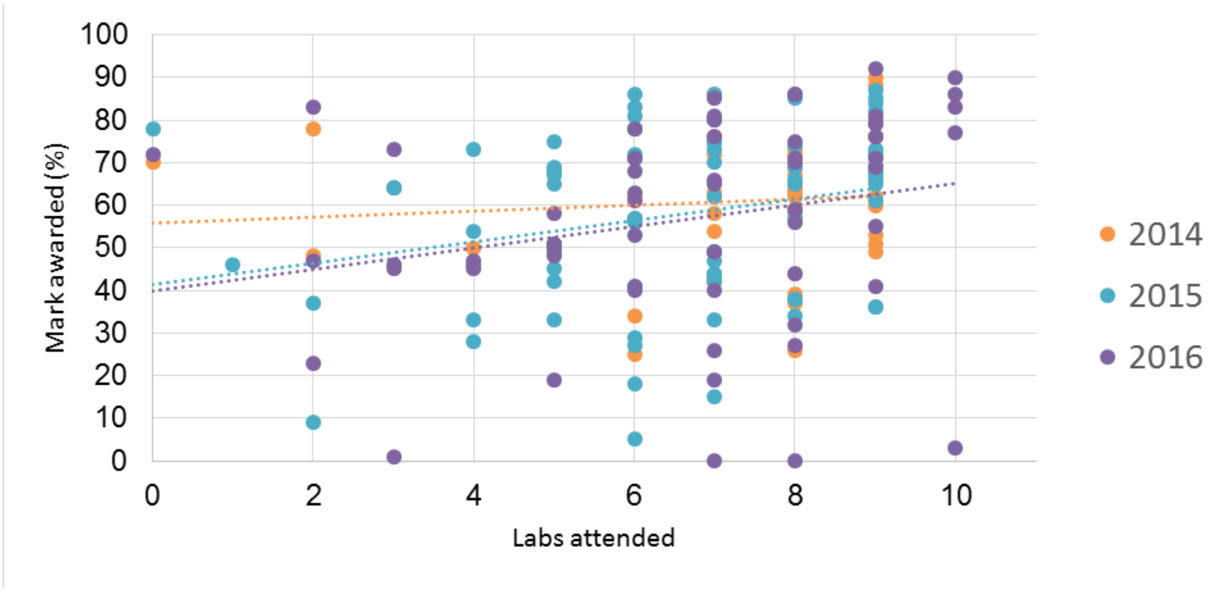

Figure 1 Attendance versus performance on the 3D Graphics module over 3 cohorts (2014, n = 60; 2015, n = 85; 2016, n = 77).

and enable us to address the question: are indicators that are not linked with any extrinsic motivators better for measuring student engagement?

Attendance and Performance

As remarked above, the effects of extrinsic motivators such as attendance can have unintended behavioural consequences. Enforcing attendance through extensive monitoring – with registers or swipe cards – may lead students to attend, but still not engage. Furthermore, the enforced attendance may create negative barriers to learning for those now forced to attend, who exhibit avoidance tactics within the learning space, or – worse in many respects – disrupt the learning of others.

Regarding attendance, Figure 1 shows data for one of our second year modules in 3D Graphics, indicating the lack of any clear correlation between attendance at programming laboratories and performance. Clearly, overall, there is a slight correlation between marks and attendance. However, the clear vertical bands for a given attendance rate show that attendance does not guarantee a good mark within a module.

Furthermore, looking at programme results against mark classification – as in Figure 2 – shows the wide range of overall outcomes, at all levels of lab engagement. Thus we can conclude that attendance at labs (with the associated monitoring of pure attendance) does not in itself improve student outcomes.

Learning Analytics: Interactions with a learning environment.

Whilst pure attendance monitoring and enforcement cannot guarantee student engagement when in a session, modern learning systems (virtual learning environments) and other online systems (such as YouTube) all offer ways to monitor levels of interaction with the system itself.

Figure 3 shows some of the data indicating the ways that a first year class interacted with materials across the 12 weeks of a teaching semester.

The graphs in the above figure reflect overall interactions: reports on individual students, including those with little or no interaction, can – and were – used to initiate communications with students to see if they had problems and why they were not engaging.

The peaks in overall activity – especially when considered in a more detailed daily format – show student behaviours in terms of preparing (or not) for lectures, and looking at assignment details.

With lecture capture systems – and online resources – that also capture interaction data,

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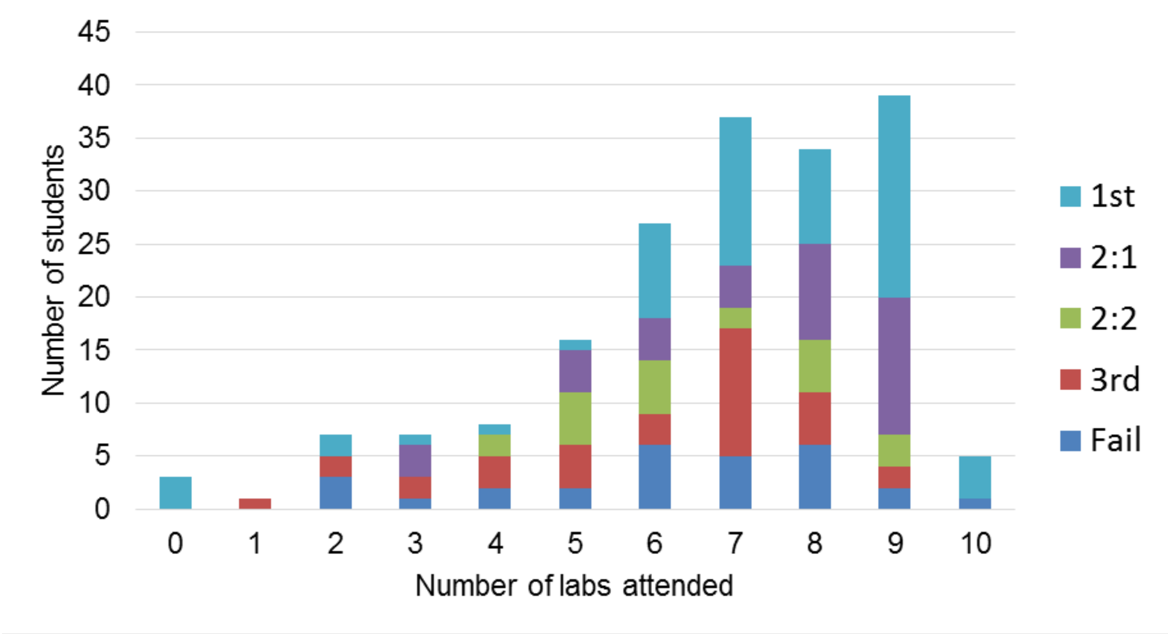

Figure 2 Lab attendance count and degree performance.

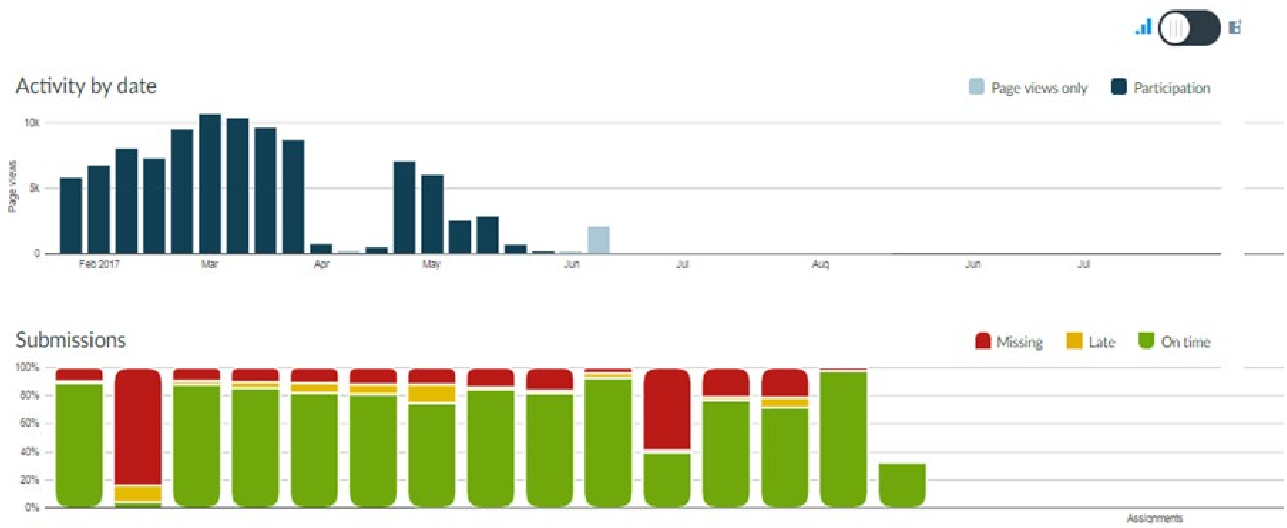

Figure 3 Learning Analytics can show student activity.

this form of learning analysis can assist teaching staff in understanding what students are actually doing, and also to identify topics and material that seems more interesting and engaging for students.

Whilst this data can help in planning and preparation, and the reporting to students of the general monitoring can potentially encourage some engagement with material, it is not pro-actively encouraging engagement. For that, one approach is through assessment.

Assessment: Formative and Summative

Utilising and adapting assessment may encourage regular and early engagement (Gordon, 2009). With summative assessment, this is clearly introducing extrinsic motivation. In designing the assessment diet, there is a need to consider whether to use formative or summative assessment. In large classes, the effectiveness of formative is more debatable, where there is unlikely to be routine formative feedback. Therefore, the challenge is will students do it at all, compared to summative assessment, where they do it for marks.

Figure 4 Assessment as a driver for engagement.

There is also a need to balance over-assessment versus having sufficient data to potentially identify and change student behaviours.

Figure 4 shows how the student behaviours around assessment mirror the nature of assessments. Weekly engagement with learning materials was encouraged through small (2% per assessment) weekly assessed computer based quizzes. The size of the green part of the bars indicate this was successful. Conversely, the early formative assessment – which included peer review of other students work – had little uptake.

Team activity – as part of a summative team project – also demonstrated good uptake in general, except for the optional activity. This shows how – in this particular module – students behaviour was highly related to assessment.

Gamification approaches – that is the use of game mechanics in teaching (Gordon et al, 2013) – can also offer ways to influence and potentially improve student engagement. This approach was used for one of the assessments in Computer Science, with students allowed repeated attempts at a summative assessment. The chart in Figure 5 shows how – given assessment options, students will repeatedly engage in order to potentially improve their marks. This example was a quiz where students were allowed multiple attempts to engage with the work, until they were content with their mark. For many, 1 attempt was deemed enough by them. However a significant number took 2 or 3 attempts, and there were several who took 7 or more. One student opted to have 15 attempts in achieving a satisfactory (to them) mark.

Source Control

What is Software Version Control?

Source control is a tool that allows teams of programmers to work on the same code files at the same time. Think of it as a way of saving work to a networked location, and being able to undo changes to any previous saved version. Source control provides version management tools to assist with issues such as identifying distinct versions of code, to be able to roll back to working versions, and to control in a managed way the combining of different parts of a set of files that may have been edited concurrently. The user (programmer) saves [i.e. commits] a version to the source control when they have identified significant changes/progress. They can add comments to a log for their own use, and for others who have access to the code repository. For an individual programmer – as used in the case study here – the key feature

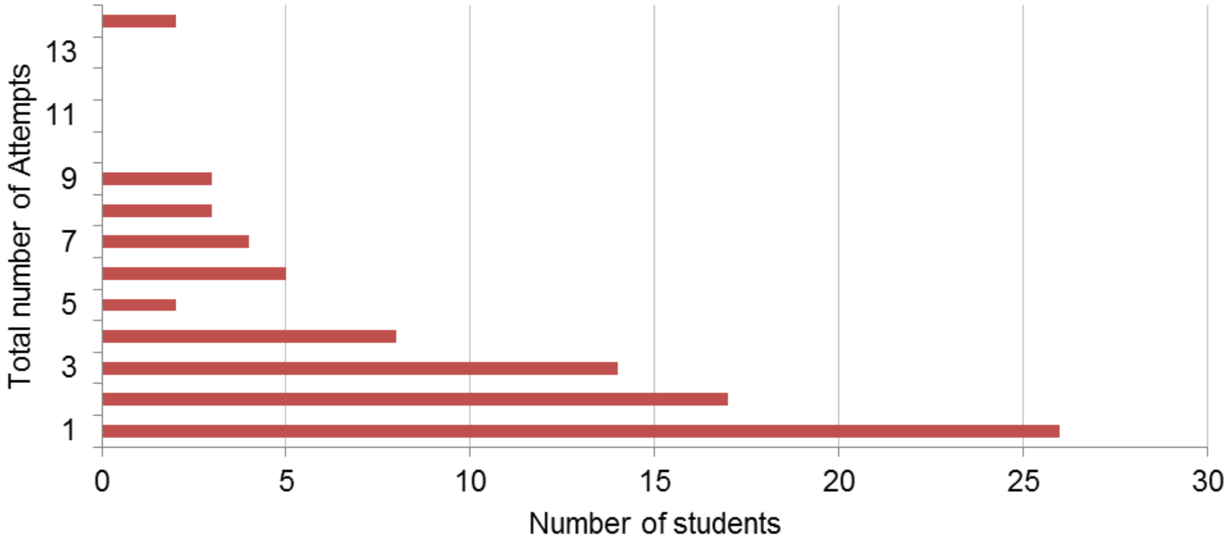

Figure 5 Number of attempts per student.

is in logging different versions, being able to access these from different devices, and being able to go back to earlier versions. Whilst source control systems are primarily there to support textual programming, similar concepts and tools for more general team and individual work are found in a range of software systems, with tracked changes in word processors, editing histories in Wikis, similar features in online editing environments such as Google Docs, and online document repositories such as Box and DropBox. Thus the kind of approach described in this paper may be applied to a wide range of disciplines.

Why use Software Version Control

For programmers effective use of source control is an important professional skill. Furthermore, for students as developers, it lowers risk of losing work and breaking their own solutions, supporting free experimentation. Finally, for educators, this allows more scaffolding of learning, enabling staff to provide more useful help whilst also auditing the development process and providing insights into student behaviours. With team development, it is possible to identify the most active (in terms of commits) team members, whilst also offering the potential to see how a project is developed.

How Software Version Control was used in the case study

Students were set a series of lab tasks, to provide a structured approach to developing a solution (program). There were prompts within the lab activities, identifying when students should commit (save or check-in) their code. Log messages were provided to encourage students to consider what they had done.

Commits were part of the lab guidance and were explained as good practice, thus motivation was intended to be intrinsic, in that they are the correct thing to do as a developer. A student could attend the lab without doing the lab activity, even if they recorded their attendance through a traditional register. Thus the record of commits can be interpreted as an indicator of engagement with lab activity. In Figure 6 we compare the number of labs attended for which students made no commits during the tow hour lab, or an hour either side. It is proposed that if a student made no commit within this four hour window it is likely that they did not engage with the work. This can be thought of as number of times students engaged with the attendance monitoring system without engaging with the work. When examining Figure 6 it is important to acknowledge two things. The first is that students may have engaged with the lab work without committing to source control. The second is to recognise that a student who attended zero labs without committing work may have attended ten labs and committed in all labs, or may have attended zero labs. From the profile in Figure 6, the number of 1st class marks is higher in

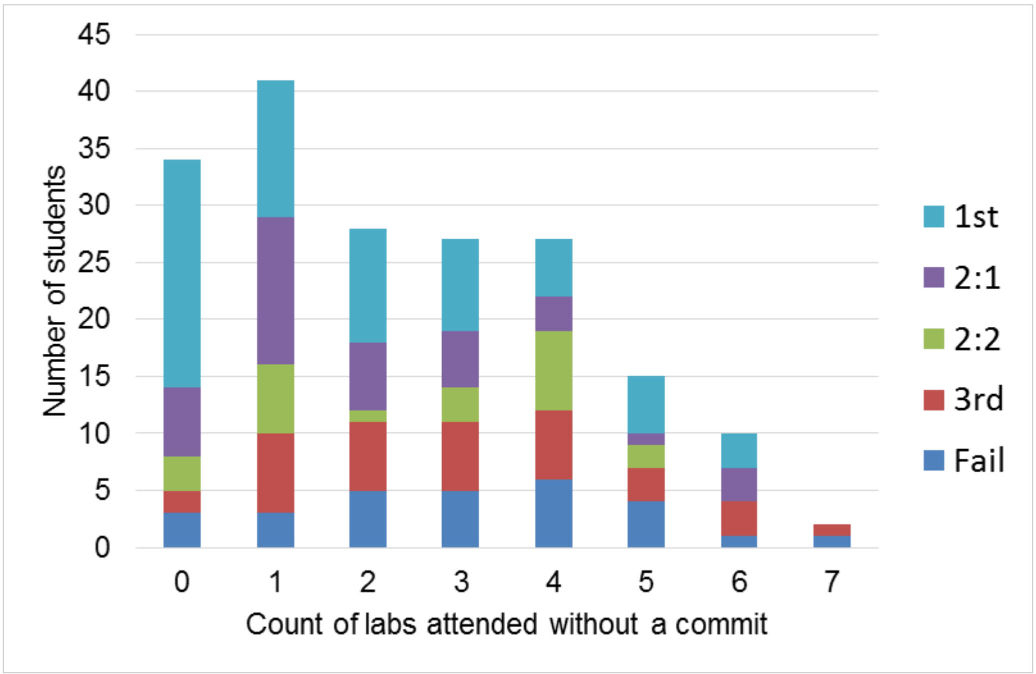

Figure 6 Module mark profile of number of students who attended labs without commits.

absolute terms for those who had no labs without committing their work (i.e. they carried out the suggested lab activities). The proportion of fails and 3rd class marks increases as we consider the bars from the left to the right, indicating that the fewer labs where appropriate source control was used, then the greater the actual number of fails and thirds, and the greater the proportion of those who failed or achieved a low mark.

Discussion and Conclusions

Inspecting Figure 6, it can be seen that those students who engaged with the attendance monitoring system the most without engaging with work through source control either failed or achieved a third class mark. Conversely, those who had no labs without a commit (i.e. they followed good practice and the lab guidance), achieved a range of marks, including the highest proportion and absolute number of first class marks. Indeed, the proportion of first and 2:1 class marks clearly decreases as the number of labs without a commit increases. This shows the potential value of this as an indicator of both student engagement and outcome.

Adding extrinsic motivators may modify student behaviour in unexpected and undesirable ways. Within education, extrinsic motivators are ultimately unavoidable where we are measuring and evaluating student performance, especially where we are grading their success. However, some forms of extrinsic motivation are more closely aligned to the desired outcomes than others.

The focus on learning analytics is typically driven by the issue of what can be easily measured and analysed. As discussed earlier, attendance data is particularly attractive as registers, swipe cards, smartphones, rfid cards or potentially image recognition can collate attendance data. The danger here is that we focus on the concept of a student attending as purely being present, rather than the more active meaning of the verb attend, being to concentrate, listen and focus. With a focus on systems that encourage/enforce passive attendance, there can be negative impacts on both those students who would choose not to attend, as they fail to concentrate or listen and do other activities, as well as those who routinely choose to focus, but have their learning disrupted. In the case study, the record of commits was used as an engagement indicator. Commits had no mark associated with them: the encouragement – i.e. the intrinsic value – was that they were part of the guidance and instruction, and that they are good professional practice.

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Mitigating strategies to avoid the problems of extrinsic motivation include:

- Aligning extrinsic motivators with desired behaviour, e.g. the use of source control that supports the programming/development activity of the students;
- Allowing students to benefit from the extrinsic, such as assessments that provide both a formative and a summative function;
- Avoiding data that creates unwanted extrinsic affects i.e. avoid attendance itself, but utilise interactions with learning resources;
- Linking extrinsic motivators now with future intrinsic motivators

Whilst the requirements to measure student learning means some extrinsic motivation is inevitable, we should consider the range of tools available to encourage desired behaviours, with a focus on those that support intrinsic motivation.

Finally, in answer to the questions posed within the paper:

- Given the different outcomes when comparing commit data with attendance, attendance alone is not a suitable predictor of student performance;
- Based on the measure of intended work and correlating that with attendance, it seems that students do engage with attendance monitoring, without engaging in the intended work;
- Engagement is best defined as focussing on and carrying out the intended learning activities;
- Indicators - such as interactions with a VLE or source control commits - are indeed better indicators of both engagement and performance.

References

Fitzgerald, H.E., Bruns, K., Sonka, S.T., Furco, A. & Swanson, L., (2016). *The centrality of engagement in higher education.* Journal of Higher Education outreach and engagement, 20(1), pp. 245-254.

Gneezy, U., Meier, S. & Rey-Biel, P. (2011). *When and why incentives (don't) work to modify behavior*. Journal of Economic Perspectives, 25(4), pp.191-210. DOI: 10.1257/jep.25.4.191

Gordon, N., (2009). *Enabling personalised learning through formative and summative assessment*. in Technology-supported Environments for Personalized Learning: Methods and Case Studies. Hershey: Information Science Publishing, pp.268-283. DOI: 10.4018/978-1-60566-884-0.ch015

Gordon, N., (2014). *Flexible pedagogies: Technology-enhanced learning*. From the report series Flexible Pedagogies: Preparing for the Future. The Higher Education Academy, January. Online at: http://www.Heacademy.ac.uk/resources/detail/flexiblelearning/flexiblepedagogies/tech_enhanced_learning/main_report (accessed 20 June 2014).

Gordon, N., Brayshaw, M. & Grey, S. (2013). *Maximising gain for minimal pain: Utilising natural game mechanics.* Innovation in Teaching and Learning in Information and Computer Sciences, 12(1), pp.27-38. DOI: 10.11120/ital.2013.00004

The Guardian (2018). *Why are students faking attendance? They feel cheated by the system.* [ONLINE] Available at: https://www.theguardian.com/higher-education-network/2018/apr/13/why-are-students-faking-attendance-they-feel-cheated-by-the-system [Accessed 10 October 2018].

Hanus, M.D. & Fox, J. (2015). *Assessing the effects of gamification in the classroom: A longitudinal study on intrinsic motivation, social comparison, satisfaction, effort, and academic performance.* Computers & Education, 80, pp.152-161. DOI:10.1016/j.compedu.2014.08.019

Nowell, C. (2017). *The influence of motivational orientation on the satisfaction of university students.* Teaching in Higher Education, 22(7), pp. 855-866. DOI: 10.1080/13562517.2017.1319811

Ryan, R.M. & Deci, E.L. (2000). *Intrinsic and extrinsic motivations: Classic definitions and new directions.* Contemporary educational psychology, 25(1), pp. 54-67. DOI: 10.1006/ceps.1999.1020

Visaria, S., Dehejia, R., Chao, M.M. & Mukhopadhyay, A. (2016). *Unintended consequences of rewards for student attendance: Results from a field experiment in Indian classrooms.* Economics of Education Review, 54, pp.173-184. DOI: 10.1016/j.econedurev.2016.08.001

Woodfield, R. (2014). *Undergraduate retention and attainment across the disciplines*. Higher Education Academy, p.45.

Zepke, N. (2014). *Student engagement research in higher education: Questioning an academic orthodoxy.* Teaching in Higher Education, 19(6), pp.697-708. DOI: 10.1080/13562517.2014.901956