Face to Face or Facebook: 21st Century University Education: A Survey

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Abstract. University education has for centuries depended on face to face interactions between academic teachers and their students. In the 21st century, social media tools such as Facebook™ consume an increasing part of the time and attention of our students, who are also more and more stressed. Meanwhile, lecture attendance is down, student part-time work is up, and what has happened to the learning? Is there an ideal amount of Facebook engagement which will maximize outcomes (learning), and engagement (enthusiasm)? We survey the relevant literature to come to some initial conclusions and propose an experimental test of our conclusion.

Keywords: University education, Facebook, Social media, Student achievement, Student engagement, Predict marks

1 Introduction

There are many possible goals in education, but for us the two primary ones are outcomes (learning), and engagement (enthusiasm) – which will lead to later learning as well as support current learning. In the area of this paper, there are a number of attributes that we could measure and a number of ways we could measure them, or measure proxies or somehow otherwise approximate these attributes if we cannot measure it directly. For outcomes, we will generally assume that we will use the student'a preferred proxy for learning, that of the grade or marks achieved in that course.

A non-exhaustive list of behaviours or actions we could measure include amount of time spent on social media, or in the classroom, the number of times certain kinds of actions such as reading or posting comments take place, or the time or proportion of time spent on those activities. In the subsequent discussion we will generally refer to social media by referring to Facebook, as it is the most commonly used such tool. We will refer to social media when discussing the work of others and want to be clear that that work did not take place with regards Facebook, or when we want to make a point that the issue being discussed has wider relevance.

The two main ways we can measure behaviours or actions is to survey the actors or observers, before and / or after the behaviour, or by actually observing and recording the behaviour.

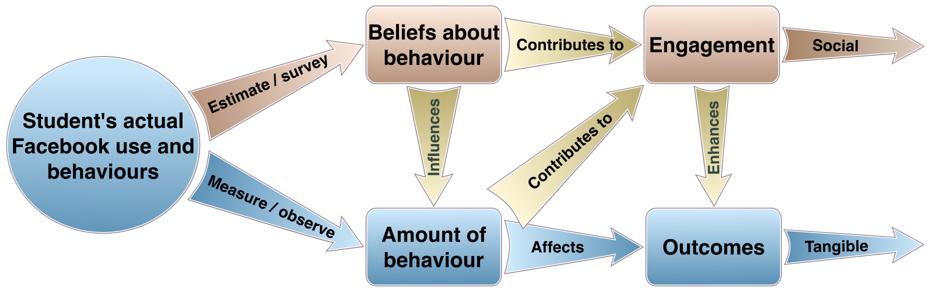

Fig. 1. Model linking behaviours to social and tangible outcomes

The analysis model we use is illustrated in Fig. 1. The lower path provides objective measurable effects, and tangible outcomes, while the upper path is clearly more related to the social aspects of the behaviours as well as its data collection. The two paths are not independent and have effects on each other. As we will see subsequently, data collection along the top path is easier, but the data collected is less useful for tangible outcome prediction.

In subsequent sections we ask questions such as can we predict student outcomes, can we predict student engagement, what are the properties of reported or actual behaviour factors which we can use to build prediction models, and can we identify the causative links between factors and engagement or outcomes?

2 Predicting student outcomes

We discuss prediction of student outcomes (marks) in this section in terms of measure data (the lower path in Figure 1), and estimate data (the upper path in the figure), respectively.

2.1 Objective data

We have done some previous work in predicting student marks in a first year Computing course [1]. The data consisted of the results from a number of laboratory exercises, assignments and a mid-term quiz all of which compose 40% of a student's mark for the subject. The marks were used in a neural network model to predict the final aggregate mark. The neural network was able to correctly classify the grade the student received based on the part-marks with a reliability of 86%.

More recent work used the Moodle [2] web-based on-line learning platform, to use students' web behaviour on Moodle to predict their final marks [3]. Table 1 shows the attributes used. The success rate in predicting final grades was 65%. The reduced prediction accuracy may be due to a less direct relationship between the measured attributes (web behaviour versus prior marks) and the predicted output (final mark).

Table 1. Attributes Used by Each Student in Summary File (from [3])

Name	Type	Description
Course	Input attribute	Identification number of the course
n_assigment	Input attribute	Number of assignments done
n_quiz_a	Input attribute	Number of quizzes passed
n_quiz_s	Input attribute	Number of quizzes failed
n_posts	Input attribute	Number of messages sent to the forum
n_read	Input attribute	Number or messages read on the forum
total_time_assignment	Input attribute	Total time used on assignments
total_time_quiz	Input attribute	Total time used on quizzes
total_time_forum	Input attribute	Total time used on forum
Mark	Class	Final mark the student obtained

2.2 Subjective data

It has been shown that previous programming experience is beneficial in terms of student achievement in a first year computing course [4]. This was estimated for 75 students via questionnaire, with summary data shown in Table 2. Note that HTML experience was controversially included as a programming language. This fits with the language we use as instructors (such as "code up some HTML") and the students' perception, yet is in fact 'just' a markup language.

Table 2. Number of students with previous language experience (from [4], modified)

	Experience	Study
None	17	29
Pascal/Delphi	29	28
Basic/Visual Basic	22	21
C/C++	34	39
Java	4	4
HTML	43	16
CGI/Perl	4	2
Other	17	15
Total	97	97

	Experience	Study
None	18	18
1 language group	10	2
2 language groups	3	1
>= 3 language groups	3	0
Total	34	21

A significant effect was found for achievement by experienced students, and this difference was related to the number of languages previously studied or used. The effect was stronger for those students who formally studied programming previously as opposed to 'mere' use of the same number of programming languages. While this work [4] did not predict final marks, the data reported would support such an activity,

and given the reported results it is highly likely that including the surveyed prior language experience would enhance the prediction. So we can posit that the use of subjective survey data at least enhances prediction of student final marks.
The connection between Facebook usage and final marks has been examined [5], in a large survey of reported detailed Facebook usage and reported GPA.

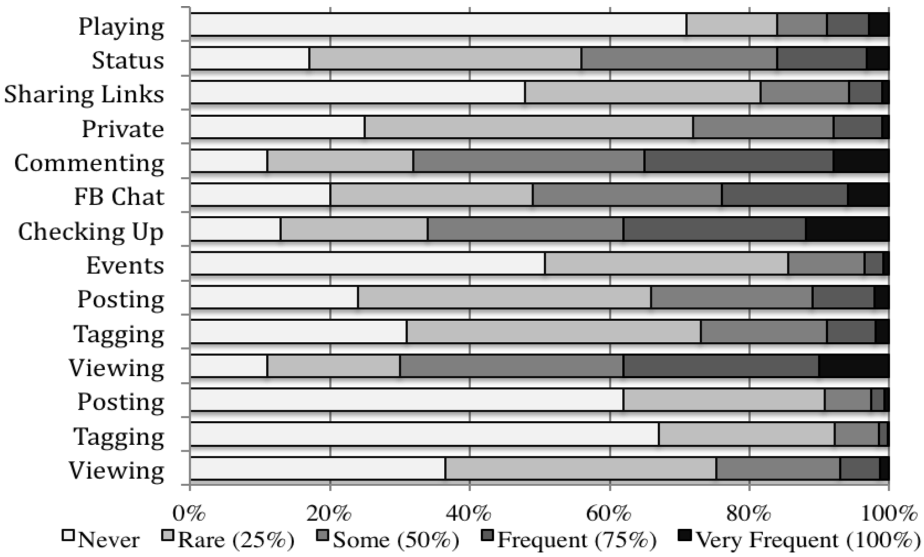

Fig. 2. Self-reported frequency of participation in Facebook activities (from [5], modifed)

The results were that Facebook use for collecting and sharing information (checking to see what friends are up to and sharing links, respectively) is positively predictive of outcomes while using Facebook for socializing (status updates and chatting) is negatively correlated. Overall time spent on Facebook is negatively related to overall GPA.

An analysis of the factors affecting the success of non-majors in learning to program [6] found that both self-efficacy and knowledge organization had a positive affect on student grade. Prior experience affected self-efficacy but not knowledge organization. In this context, we can understand the relatively low accuracy of results in [3] better, where here knowledge organization relates to prior study. Students' self-efficacy beliefs come from four sources of information [7]: personal experiences of mastery; second-hand experiences (observation); verbal persuasion, encouragement by others etc; and emotional arousal. Of the sources of self-efficacy beliefs, personal experience of successfully mastering a task is the most direct and most powerful. Social media benefits could only arise via persuasion and this is at most of minor positive benefit.

Another study on on-line achievement [8] found that, as we would now expect, prior GPA is the best predictor of results, and that while factors related to self-efficacy had either no effect or were positively correlated, desire for interaction was negatively correlated with results. This accords with the negative effect of the quantity of on-line social interaction negatively correlating with student achievement, and suggests that the social interaction and course achievement goals are not the same or even similar, and that time spent on one is at the cost of the other.

3 Predicting student engagement

We could not find any studies linking measure data to student engagement. This is a possible hole in the literature, which could do with investigation. There is an abundant literature on estimate / survey data relating numerous factors to student engagement. We focus on three indicative studies particularly relevant to the focus of our work.

3.1 Estimate data

A study using job design and work stress theories examined the relation between psychosocial work characteristics, well-being and satisfaction, and performance [9].

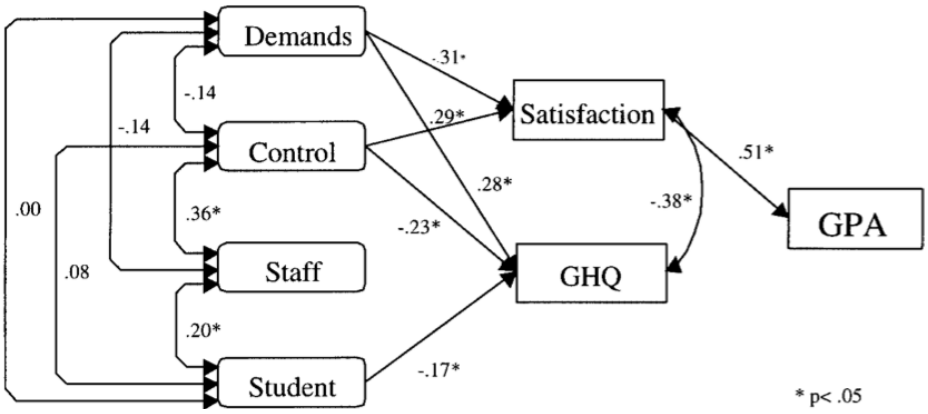

Fig. 3. Relating job characteristics, psychological outcomes, and performance in university students (additive structural model from [9], GHQ = General Heath Questionnaire [10])

Social interaction is an important motivational factor for 'job design', which relates to satisfaction here, which has a statistically significant impact on GPA. A difference was found with regards to quantity of interaction versus quality of interaction, with as expected the latter being the most effective. This is consistent with studies on student achievement in that quantity of hours was generally found to be negative and that the higher quality of interactions are most significant. The study also concluded that both prior to examinations (expected) and at the commencement of the subsequent semester, high levels of distress and demotivating effect of low satisfaction were found, which may lead to underachievement. This is relevant to our goals as it known that high levels of stress negatively affect students' cognitive processes such as concentration and memory [11] which must clearly impact on their ability to learn and hence on student achievement overall.

On the other hand, it was found that overall time spent online including Facebook was positively correlated with student engagement [12]. It is possible this difference in the more recent survey is due to better on-line targeting of time in general, though we consider it more likely to be the difference between prediction of achievement as opposed to prediction of engagement.

4 Reliability of measures for student outcomes and engagement

The major limitation in the reliability of most of the work in the literature is the reliance on self-report data. Media use is thought to be particularly difficult to measure accurately using self-report data [13]. Self-reporting of GPA is also fraught and is readily affected by priming [14], such that participants primed with attachment security were statistically significantly less willing to lie about their GPA in an achievement context, than those primed with attachment anxiety. Yet as we have seen that high levels of distress are often concomitants of student study life, we must be skeptical of correlations and results from surveys without other forms of validation.

5 Causation

A major limitation of all of the studies discussed is that they are cross-sectional and correlational in nature, and therefore it is impossible to determine the causal mechanisms between social factors / social media / Facebook use and engagement or achievement [8, 12, 5]. Of course, while these designs are inappropriate for drawing causal inferences from the data because of the lack of a comparison condition, they are perfectly appropriate for investigating relationships [8]. The key point for us is that both large numbers of hours of Facebook use and low achievement may be correlated, they may be the causal outcome of some other factor, hence reducing the number of Facebook hours may have no or even detrimental effect on achievement.

In our own prior work [1], using student part-marks to predict their final mark, we used causal indices to identify the rules being used by the neural network in making the high quality conclusions we achieved. It must be noted that this causation is in terms of the neural network model making the prediction and says nothing about the real world setting being modeled by the neural network. Thus, we had available some parts (the part-marks worth 40%) of the final mark, and clearly the addition of part-marks and exam marks produces the final mark. We could perhaps consider these part-marks to be 40% causal to the final mark? Anecdotally, a predicted high mark could cause a lower than predicted final mark due to complacence, whereas a lower predicted mark than desired could lead to a greater effort and a final mark higher than that predicted. By these arguments we conclude that the objective measures (lower path in Fig. 1) have no intrinsic greater claim to having identified causation of student levels of achievement.

6 Conclusion and proposal for further work

We can conclude that there appears to be some approximately ideal amount of Facebook time, which is correlated with student engagement, though this number of hours has not as yet been identified. We can also conclude that measures of actual behaviour are needed (as opposed to self-reporting) to be able to produce reliable predictions of student performance. We have seen that self-reporting is fraught is the areas of interest to us.

For progress to be made which can be relied on pro-actively to improve student achievement and/or engagement, we believe it is necessary to: i) measure actual Facebook behaviour including patterns of behaviour; ii) measure student achievement (marks) as well as engagement (necessarily will need to be done primarily by questionnaire, but should be enhanced by measures of participation in voluntary study activities); iii) plausible causative models developed; and iv) testing of causative models by interventions. So far, none of these steps have been taken, to our knowledge, and reported in the literature. Our future work is in this direction, we have already begun work on steps *i* and *ii*.

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