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Mining for Meaning: Detecting Behavioural Patterns in Student Spatiotemporal Data

Senorita JOHN[a*], Russell BUTSON[a] & Rachel SPRONKEN-SMITH[ab]
[a]*Higher Education Development Centre, University of Otago, New Zealand*
[b]*Graduate Research School, University of Otago, New Zealand*
*senorita.john@postgrad.otago.ac.nz

Abstract: The life of an undergraduate student is typically portrayed as one of studying, attending classes, and socialising. However, these types of depictions tend to mask the complexities associated with student life/learning. This study aims to investigate the degree to which the repetitive, mundane, and seemingly insignificant actions that define student daily life shape their academic development. In this talk we present a more holistic perspective of the students' educational experience grounded in daily student action. Drawing on the theoretical forms and concepts of Space-Event-Movement articulated by Bernard Tschumi in his book The Manhattan Transcripts, we went about transcribing a) the spaces in which students spend their time, b) the activities (events) they undertake in these spaces, and c) the movements or connectors that bind these spaces. Rather than following the traditional approach within higher education research of asking people questions, we experimented with new advances in digital data capture methods (e.g., reality mining through wearable sensor-based devices). This allowed us to harvest students continuous naturally-occurring behavioural data – 'what they were actually doing, rather than their perceptions, or what they say they did. Given the changing nature of higher education, it seems essential that we explore new and innovative ways to examine and probe the academic development of our undergraduate students. In this way, we hope the findings of this study will act as a catalyst to raise the profile of behaviour-centric research in shaping our understanding of student experience, development and wellbeing.

Keywords: Reality mining, student life, undergraduate experience, health science education.

1. Background

Universities are having to adapt to a broadly changing world. They are being influenced by powerful forces, such as: the proliferation of digitalisation; globalisation; massification; increasing student mobility and diversity; new patterns of financing higher education; and innovations in teaching and learning technologies (Altbach, Reisberg, & Rumbley, 2010; Ramsden, 2008). In New Zealand, there is also increasing pressure for universities to be more efficient and productive and better aligned to serving national and international imperatives (New Zealand Productivity Commission, 2017). Likewise, the student body is also experiencing change (Liu & Tee, 2014; Fitzgibbon & Prior, 2010; Ramsden, 2008), driven by a growing demand for 21st century competencies that include: diversity of learning and innovation skills; information, media and technology skills; and life and career skills (Kaufman, 2013; Larson & Miller, 2011). This is reflected in the shift in educational research from a focus on teaching, to learning, and more recently to student experience. However, our understanding of students' wider daily practices, both in and outside of academia, remains relatively naïve.

Generally, ideas surrounding student practices in higher education are 'fuzzy' given that the majority of a student's time is not spent in the classroom. Yet traditionally, student-focused research has concentrated on learning as a result of teaching; exploring the impact of teaching practices and the impact of instructional design models. We argue that to understand student experience requires investigations that extend beyond the lecture theatres, laboratories and classrooms, and include both the academic and non-academic realms. Understanding the student experience from this more holistic, experience-based perspective has the potential to provide new insights into the practice of learning.

This study aims to define 'educational ecosystems' for a group of undergraduate health science students by tracing their everyday practices (including the seemingly inconsequential or mundane) over an academic semester. This will allow us to assemble academic, social, psychological and behavioural aspects of these student's daily experiences in the hope of discovering new insights into student learning for the 21st century. This paper reports on the early stages of the research, including the rationale, research methodology and a number of preliminary findings.

2. Methodology

The study is established on the precepts and practices associated with 'reality mining' (Eagle & Pentland, 2006) and adopts an ideographic approach focused on individual cases rather than grouped or aggregated data. Rather than following the traditional approach within higher education research of asking people questions, this study experiments with new advances in digital data capture methods (e.g., through wearable sensor-based devices). This allows us to harvest students' continuous, naturally-occurring behavioural data—what they are actually doing, rather than their perceptions of what they think they are doing (John & Butson, 2016; Sim & Butson, 2014; Paretta & Catalano, 2013).

The process of mining behavioural reality through harvesting digital sensor data allows researchers to investigate the extraordinary detail of behaviour with exceptional spatiotemporal resolution (Wu et. al., 2014; De Montjoye et. al., 2013; Batty et. al., 2012). The explosion of digital devices offers a fertile landscape to employ various reality mining approaches. Tapping into these rich data sources can provide unique insights into human daily activity patterns, the topology and dynamics of physical social networks, and the flow of information between individuals (De Montjoye et. al., 2013; Noulas et. al., 2012). However, the systematic profiling of complex life styles and educational ecosystems that students inhabit represents an extremely demanding challenges. To overcome these challenges, we harvested digital trace data produced by various digital devices that offer insights into individual student the spaces, events and movements.

Employing a theoretical framework grounded in the concepts of Space-Event-Movement (SEM) allows us to transcribe: a) the spaces in which students spend their time, b) the activities (events) they undertake in these spaces, and c) the movements or connectors that bind these spaces. Developed by the architectural theorist, Bernard Tschumi (1976), the SEM framework allows us to address the intentions and purposes that underpin—why a person happens to be in a particular place/space at a particular time, what they are doing, how they came to be there and where they intend to go next (Hornsby & Yuan, 2008). SEM coupled with Reality Mining has the capability to construct real-world meaning from large volumes of digital trace data, an essential process in deep behavioural profiling.

3. Significance

Given the anticipated changing state of higher education and the shifts occurring in student cohorts (New Zealand Productivity Commission, 2017; Liu & Tee, 2014; Fitzgibbon & Prior, 2010; Ramsden, 2008), gaining an understanding of the demands and changes students are currently undergoing would appear to be essential. In particular, understanding student activity in order to uncover insight and relevance from what often seems to be repetitive, tedious and mundane encounters typical of daily student life.

As stakeholders, students play an important part in the process of higher education. For this reason, students, faculty and administrators have a vested interest in understanding what goes on in the daily life of a student. While there is considerable research into understanding aspects of teaching and learning, these have tended to be focused on the construct that learning is the result of teaching. In this way, the real or true nature of the student's educational experience (outside of teaching), appears to receive little attention. For this reason, the links between a student's academic, social, psychological and behavioural characteristics remain unclear. This study aims to change that. Possibly the first of its

kind, we believe this study will act as a catalyst to raise the profile of students' daily activities, and in so doing identify core activities (academic and non-academic) that are significant to a student's performance and wellbeing.

4. Fieldwork

A convenience sample of 21 undergraduate health science students were recruited for a period of one semester (4 first year, 2 second year, and 15 third year). The datasets are described in more detail below:

Contextual data (photograph data): Photos are an ideal way of capturing rich observations of people, places, and events and sometimes even moods and feelings in the field (Warren, 2002). They can augment the ability to research, describe, and symbolise the participant's world. In this study, the photographs are generated by the students using small clip-on cameras that take a photo every 30sec. These first-person views are used to create an inventory of the student's daily activities. The aim is to generate a photographic record of the student's contextual environment over the data capturing intervals.

Movement data (GPS traces): GPS data is used to determine daily movement traces of students, the places they visit and spend time in. The application used (EasyTrials) is a mobile application that provides high quality location and time information. This application helps determine exactly where the student is at any moment in time. The participant uses the application to output the positioning information as a CSV (Comma Separated Values) file, which is transferred via email to the researcher. The researcher then integrates this information into Google Earth, which displays the movement traces on the relevant Google location map.

Computer usage (influence of technology): Computer usage data is used to understand how students spend their time while using technology/computers. Software is installed on participant's computers to record the date, time, duration and type of computer programmes used. The application (RescueTime) allows the analysis of computer usage habits. One of the most important things about RescueTime is that there is no data entry. Once installed on the student's computers it automatically tracks usage by application/date/time and duration.

Mood data (psychological measure): This dataset includes the use of technology for tracking and representing emotions through user-initiated approaches. The focus of this dataset is to understand emotion and mood as affective reactions to an event, typically short-lived and directed at a specific object. To be able to do so applications are installed on the student's cell phones to track and record their mood. Mood tracker applications allow the logging and tracking of moods periodically through the day. The application (Moodlytics) presents the analysis of mood journals through charts and graphs.

Each participant was provided with an auto-camera, GPS phone application, software for computer usage tracking, and a mood-tracking phone application. They were also expected to meet for 30mins each week to review the data gathered. These sessions were also used to develop the student profiles. Data for this study was collected over a 5-month semester period (Feb 2017 – June 2017).

The presentation will elaborate on the data capture methods employed, the challenges experienced and share some preliminary findings.

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