

Held-by-hand learners: A survey of technologies to support positive behaviours of Higher Education students today

Wilde, Adriana¹; Ed Zaluska²

Web and Internet Science Group
Electronics and Computer Science
University of Southampton
United Kingdom, SO17 1PG

¹ *agw106@ecs.soton.ac.uk* ² *ejz@ecs.soton.ac.uk*

ABSTRACT (RESUMEN)

Computing and information technology in general have been traditionally used in higher education in a somewhat limited way, using fairly static configurations (e.g. fixed equipment, fixed location, fixed access times). However, at present there is a widespread adoption of sensor-loaded, powerful, mobile devices, which have the potential to overcome technological limitations in traditional education. Furthermore, for the majority of current university students there is a high degree of digital literacy, therefore the adoption of mobile technology to facilitate their learning is an interesting proposition. Such a technology can enable greater access to learning resources as well as a greater understanding of student behaviour. Achieving such an understanding could be used to help students, by prompting them into adopting behaviours identified as likely to increase their chances of academic success. This paper explores the state of the art in context-aware technologies and their existing use in education, and discusses directions of study for behavioural interventions to higher education students using learning analytics on data gathered by these technologies.

KEY WORDS (PALABRAS CLAVE): pervasive computing, hand-held devices, higher education, digital behavioural interventions, context-aware technologies, educational technology.

1. INTRODUCTION

Recent developments in mobile technologies have allowed a high integration of information processing, connectivity and sensing capabilities into everyday objects. It is now easier than ever to collect, analyse and exchange data about our daily activities: revolutionising how humans live, work and learn. This is particularly true amongst higher education students today, who already generate a rich “data trail” as they navigate their way through technology towards successful completion of their studies.

Learning analytics focusses on the use of institutional data about their students to promptly identify poor performance so that actions that can be taken and facilitate success. Struggling students in particular need to be directed to be able to complete their courses more successfully (Baepler and Murdoch, 2010), as the failure to do so comes to a great cost, not only to these students but to their institutions. This is a difficult issue, as measures of success are usually limited to traditional indicators such as progression and academic performance. The reason is that for a student, an educational institution and the wider society, “success” would have to be defined by retention, level of engagement and contentment as well as achievement of higher marks.

One valid approach to understanding how students learn may be to use technology to gather data about activities from which the interests, motives and behaviours of successful students could be inferred. A second step would use these findings to inform aspiring students. The technology available for collecting activity data is not only becoming more diverse and powerful but it is also becoming widely available at a decreasing costs, hence increasing the potential for the development of pervasive systems. Indeed, the greater affordability of smartphones and the ubiquity of the internet not only means that all students can access learning materials anytime and anywhere (which does not mean that they do) but, more than ever before, that we can learn more about student habits and context. What do students actually do?

The application of pervasive computing in the area of education exploits both the opportunity of the ubiquity of devices and digital natives' interest in technology. Indeed, as stated earlier, there has been a great amount of research in this direction, with numerous examples of the application of pervasive technologies in pedagogy:

- To assess students (Dong *et al.*, 2007);
- To increase access to content and annotation capabilities in support of peer-to-peer learning (Yang, 2006);

- To inform the learning activity design taking student context into account (Hwang, Tsai and Yang, 2008);
- To increase interaction by broadening discourse in the classroom (Anderson and Serra, 2011; Griswold *et al.*, 2004) or by playing mobile learning games (Laine *et al.*, 2010);
- To enrich student learning experiences indoors and/or outdoors with digital augmentation (Rogers *et al.*, 2004, 2005);
- To enable ubiquitous learning in resource-limited settings, and observing the influence of new tools in the adaptation of learning activities and community rules (Pimmer *et al.*, 2013).

These examples demonstrate the possibility of applying such technologies in education. However, they had not set out to use contextual information in order to predict or even understand student behaviours. To address this shortcoming, we investigate context-aware computing methods and techniques that have been applied successfully in the areas of healthcare, assisted living and social networking, and apply them to higher education. Researchers' findings in context acquisition (Owens *et al.*, 2009; dos Santos *et al.*, 2010) could be applied in this area of research. In our opinion, the use of novel techniques from ubiquitous computing into an investigation of student behaviour is worth exploring.

The remainder of this paper is organized as follows: In Section 2 we consider the characteristics of our learners; in Section 3 we explore the state of the art in context-aware technologies and their existing use in education. In Section 4, we consider the type of data that is typically used; whilst in Section 5 we discuss future trends based on previous research. Lastly, section 6 presents conclusions and future work.

2. ARE OUR LEARNERS “DIGITAL NATIVES”?

The term digital natives (Prensky, 2001a), widely used above many others¹, has been used to characterize a perceived shift in learning habits and interaction with the digital world as a generational trait. The term itself is linked to the emerging digital technology of the 1980s and 1990s within which the majority of the individuals within

¹ Terms include: millennials, generation Y, trophy kids, net generation, net geners, echo boomers, first digitals, dot.com generation, nexters, cybercitizens, netizens, homo digitalis, homo sapiens digital, technologically enhanced beings, digital youth and the “yuk/wow” generation (Hockly, 2011; Berk, 2009; Dawson, 2009).

the population of interest were born, “typically between 1982 and 2003 (standard error of +/-2 years)” (Berk, 2009). By this definition, members of this group therefore include the great majority of students in higher education today. Furthermore, according to Prensky (2001b) many of them may even process and interpret information differently due to the “plasticity of the brain”. If so, what were regarded as effective study habits and behaviours in previous generations may not necessarily be as effective for the current generation of students.

Calling this group a generation might be an overstatement, since only a fraction of the world population access digital technologies to achieve ‘native’-like fluency in their use, but they can be seen as a population (Palfrey and Gasser, 2010). Furthermore, education, experience, breadth of use and self-efficacy are more relevant than age in explaining how people become “digital natives” (Helsper and Eynon, 2010). Furthermore, the use of the term digital natives may well be replaced by the use of the term digital residents and its counterpart digital visitors (White *et al.*, 2012).

Arguably, however, describing today's students as digital natives/residents is an overgeneralisation. As Jones and Shao point out, “global empirical evidence shows that today's young students repeatedly prove to be a mixture of groups with various interests, motives, and behaviours, and that they never cohere into a single group or generation of students with common characteristics” (2011).

Despite the lack of consensus, one thing is certain: students of today (digital natives or not) have unprecedented access to a range of technologies that have the potential to, firstly, help understanding how students learn, and secondly, improve their learning experience further. It is therefore worthwhile investigating what behaviours and activities are most effective for students today.

Having said that, we also agree with White *et al.* (2012) in that a continuum rather than a dichotomy is a more useful typology, and that individuals are placed along such a continuum depending on many factors other than age. However, it has also been observed that many within this population are not only engaged in digital technologies in a daily basis, in their world there have always been computers and various forms of digital technologies, and they do not know of a world without computers. They have digital devices, which are always-on and always-on-them, being essentially ‘tethered’, as identified by Turkle (2008). Even with the proviso that this behaviour is not necessarily generalizable “outside of the social class currently wealthy enough to afford such things” (2008), it is an observable behaviour that is increasingly common amongst

individuals from this population, as digital technologies become more affordable than ever before. As a consequence, the opportunities afforded by new technologies in communication and education must be embraced, not ignoring the challenges and limitations that they bring too, as emerging technologies can be disruptive at a societal level, as Cabero (1996) reflected, and educators must consider both facets in their adoption.

3. HANDHELD DEVICES IN THE CLASSROOM AND BEYOND

There is a great variety of systems based on handheld devices that have made their way into the classroom. Examples are electronic voting systems, also known as audience response systems, which comprise of a USB receiver and a set of handheld devices commonly known as zappers (in the UK) and clickers (in the US). These are small transmitters of a similar size to a small calculator (Figure 1), which can be used by students to transmit their answers to questions in large classes (Caldwell, 2007; Wilde, 2014a), therefore increasing student participation in lectures, and fostering discussion and attentiveness. However, there are some problems associated with their adoption (besides their expense) as they require significant setting-up time and administration, as well as the design of effective questions.



Figure 1: A Turning Point zapper

Moreover, zappers have been reported to add little value in time-constrained lectures where a great amount of content needs to be covered (Kenwright, 2009), which suggests that their substitution by personal digital assistants (PDAs) and smartphones may still offer little value in engage students. Despite these misgivings, Estrems *et al.* challenged the common preconception that these kinds of devices are disruptive for learning, and rather than banning the use of students' phones, they encouraged their use in the lecture as zappers (Estrems *et al.*, 2009). As a result, engagement levels rose as these devices were transformed into a means of interaction with each other, with the

lecturers, and with the learning material, rather than merely the ‘outside world’ and other distractions. Other works also incorporate with success the use of Wi-Fi enabled mobile devices in the classroom (Anderson and Serra, 2011).

Arguably, this application could be perceived as another instance of computer assisted instruction², where digital content is used in teaching and learning. The majority of these systems have a client-server architecture supporting teacher-centric models of learning (common scenarios have teachers producing the content while students ‘consume’ it) (Yang, 2006). To put this assertion in context, pedagogic conceptions of teaching and learning are usually understood in the literature as falling into one of two categories: teacher-centred (content driven) and student-centred (learning driven) (Jones, 2011, and references therein). Figure 2 shows these orientations as overarching the main five conceptions of teaching and learning which act as landmarks alongside a continuum of roles in learning. Deep learning occurs at the bottom end of the spectrum, as opposed to shallow learning which occurs at the top end.

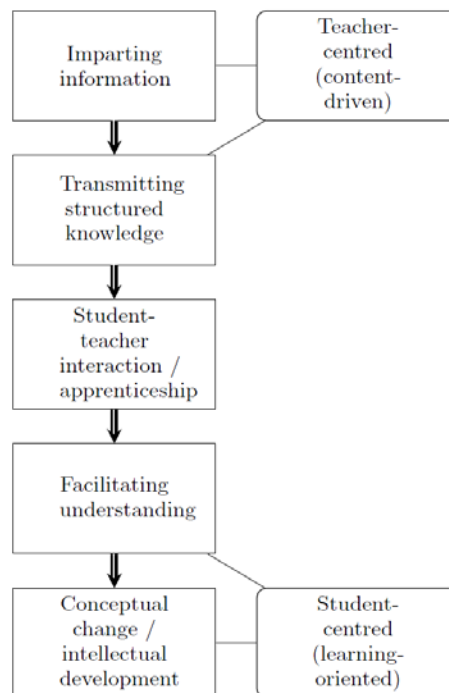


Figure 2: Multi-level categorisation model of conceptions of teaching (adapted from Kember, 1997)

However, computer assisted learning can be used not only to deliver content, but also to assess student progress and to provide feedback. For example, (Piech *et al.*,

² Not to be confused with e-learning, which is used only when the content is accessed over the Internet, rather than the general case discussed here. More on e-learning in (Hughes, 2007; Jones, 2011).

2012) use machine learning techniques to create a model of learners' progression through a piece of coursework in a Computer Science course. Rather than being merely used as a medium to access content, White and Turner (2011) investigated how smartphones can be leveraged to enhance computing education, exploiting their students' exceptional interest and excitement for building smartphone apps. Despite the name of the article ("Smartphone Computing in the Classroom"), the technology is used beyond the lecture theatre, and students improve their programming skills by using the smartphone as platforms to showcase their prototypes.

Also important is the use of smartphones as sensor carriers. What not long ago required cumbersome sensing equipment, often carried in backpacks (Amft and Lukowicz, 2009; Wilde, 2011), is now achieved using sensors within a smartphone, already carried by the 'tethered', digital natives who are the subjects of interest of this research. Contextual information can be inferred from the sensor data hence gathered, and once the context has been characterised, relevant services could be offered as in, for example, location-based services.

Moreover, it has been long accepted that "there is more to context than location" (Schmidt *et al.*, 1999). Contextual information broadly falls into one of two types: physical environment context (such as light, pressure, humidity and temperature) and human factor related context, such as information about users (such as habits, emotional state, and bio-physiological conditions), their social environment (such as co-location with others, social interaction and group dynamics), and their tasks (such as spontaneous activity, engaged tasks, goals and plans) (Schmidt *et al.*, 1999). Context acquisition is, however, important not just because of the possibility to offer customized services that adapt to the circumstances. Context processing can increase user awareness (Andrew *et al.*, 2007), and thereby prompt alternative actions to better achieve a desired goal given the current context. This would be a suitable foundation for a behavioural intervention which is aligned to the user's goals, and the smartphone is a suitable sensing platform (Lane *et al.*, 2010) which could be used to understand users' behaviour, as well as supporting them in achieving their higher goals, such as academic success.

4 ON WHAT DATA?

In the previous Section smartphones were considered not as mere distractions to learners but as potential tools to gauge knowledge and facilitate understanding, and as

sensing platforms. Equipped with ambient light sensors, proximity sensors, accelerometers, GPS, camera(s), microphone, compass and gyroscope, plus Wi-Fi, Bluetooth radios, a variety of applications can be built to gather a great range of sensed data. Thanks to their communication and processing capabilities, smartphones could support a sensing architecture (Lane *et al.*, 2010).

In addition to the data that can be collected implicitly (i.e. without explicit intervention from the user) via smartphones, the possibility of incorporating user-generated data is also valuable. Indeed, life annotations (Smith *et al.*, 2006) and ‘lifelogging’ (Smith *et al.*, 2011) can be used successfully to support “ubiquitous learning” (Ogata *et al.*, 2011). These researchers proposed the use of a ubiquitous learning life-logging system as a record of learning experiences with photos, audios, video, QR-codes, RFID tags and sensor data such as location, which can be used for reflection. Other data that might be readily available and that could be used for learning analytics, include student records held by the institution as well as course management system audits. Learning analytics could be applied to these also to study scholarly innovations in teaching and learning. According to Baepler and Murdoch (2010), the term academic analytics was originally coined by the makers of the virtual learning environment (VLE) Blackboard, and it has become widely accepted to describe the actions “that can be taken with real-time data reporting and with predictive modeling” which in turn helps to suggest likely outcomes from certain behavioural patterns (Baepler and Murdoch, 2010). Educational data mining involves processing such data (collected from the VLE or other sources) through machine learning algorithms, enabling knowledge discovery, which is “the nontrivial extraction of implicit, previously unknown, and potentially useful information from data” (Frawley *et al.*, 1992). Whilst data mining does not explain causality, it can discover important correlations which might still offer interesting insights. When applied to higher education, this might enable the discovery of positive behaviours, such as for example, whether students posting more than a certain number of times in an online forum tend to have higher final marks, or whether attendance at lectures is a defining factor for academic success.

This section has set out the background to the general problem that concerns this research, which can now be formulated and specified in the following Section.

5. DISCUSSION

Having surveyed the type of data and techniques that can be used to understand and predict student behaviour, we can now dissect the general problem stated in the introduction into two questions for discussion. Firstly, could we infer the interests, motives and behaviours of successful students? Secondly, could we use these findings to prompt students (under the assumption that it would be helpful), prompting them into good habits and behaviours?

Inferring the interests, motives and behaviours of successful students

Most context-aware ubiquitous systems use location as the most important contextual information available. Indeed, there is a wealth of research and commercial products which offer location-based services, which focus on the use of readily available information relevant to users in a given location.

Not yet so well exploited, although gathering significant scientific interest, is the use of physical activities as contextual information. Other sources of contextual information that can become readily available include the use of social media and learning analytics. Additionally, using sentiment analysis on social media could help capture users mood and general outlook over the observable period. Data mining algorithms could be applied over collected data, however, the “ground truth” measure of what constitutes a successful student needs to be established beforehand, and as explained earlier, it is in itself a very difficult question. Proxy measures of success might be used, such as academic achievement, but other aspects of student life such as level of engagement and contentedness should be also taken into account for a more complete portrait of a successful student.

Using ubiquitous computing to improve the learning experience

Learning can be supported using ubiquitous computing, as considered in the previous Section. Any knowledge about existing behaviours, alongside with those of their peers as a whole, as well as that of “successful students” would be very valuable to inform students' learning. Triggered by contextual clues, positive “nudges” could be advantageous to aspiring students to better achieve their goals of academic success (Wilde, 2016).

In the context of behavioural interventions, the term “nudge” (Balebako *et al.*, 2011; Acquisti, 2009; Thaler and Sunstein, 2008) describes “any aspect of the choice architecture that alters people's behaviour in a predictable way without forbidding any options or significantly changing their economic incentives.” By choice architecture

these authors refer to the environment (either social or physical) in which individuals make choices. There is an element of low awareness on the part of the individual of such architecture, so the individuals are still exercising their free will when making choices, however such a choice might be different without such an intervention.

6. CONCLUSIONS

This paper has explored the confluence of two important research areas: ubiquitous computing and pedagogy, which come to the aid of modern Higher Education institutions which devote great efforts to support students and encourage them to succeed, by making learning materials widely available to their students, for example. Furthermore, the greater affordability of smartphones and the ubiquity of the Internet not only allows students to access learning materials anytime and anywhere (although students may well not see this as the primary benefit of such technologies), but also allows academics to learn more about student habits and context than ever before. In other words: what do students actually do and could this information empower them to do better?

One valid approach to understanding how students learn may use technology to gather data about the conditioning factors for their success as well as the behaviours they adopt in their student lives. A second step would then use these indicators to predict student success in time to perform an intervention on those students identified as “at risk”. The technology available for collecting activity data is not only becoming more diverse and powerful but it is also becoming widely available at a decreasing costs, hence increasing the potential for building “Big Data” collections on which sophisticated prediction models could be devised.

We have identified an area of research yet to be exploited fully, which is combining contextual information (to be gathered via smartphones) with learning analytics in order to understand students' behaviour and then to use this analysis to nudge students into behaviours that would increase their chances of academic success. We then formulated two specific research questions: “how to infer the interests, motives and behaviours of successful students” and “how could ubiquitous computing improve students' learning experience”, propositioning that smartphone can be used to close the loop and provide information about what successful students do. The implications of this research, whilst at present limited to students of one university, are wide and deep,

as any findings will help advancing our understanding of human behaviour in the digital age.

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ABOUT THE AUTHORS:

Adriana Wilde

Adriana has obtained a BSc(Hons) in Computer Science from Universidad Central de Venezuela, a PGCE (in Post-Compulsory Education and Training) from the University of Southampton, UK, and a MSc in Distributed Systems from the universities of Bern, Neuchatel and Fribourg (Switzerland). She is a Fellow of the Higher Education Academy, a student member of the ACM and the IEEE, and a 2013 Google Scholar finalist for Europe, Middle East and Africa (now Women Techmakers EMEA). Her current research interests are learning analytics and pervasive computing, though she lectures in a broader number of subjects in Computer Science, such as Human-Computer Interaction, Cybersecurity, Distributed Systems and Networks. Adriana is currently a Teaching Fellow in Computer Science at the University of Southampton and a PhD candidate with the Web and Internet Science group, working under the supervision of Ed Zaluska.

Ed Zaluska

Ed Zaluska (B.Sc C.Eng FIET SMIEEE) is an experienced academic with over 100 publications spanning 40+ years. His research interests in distributed computing range over a wide range of topics. These include distributed file systems including distributed data management (e.g. the CERN support infrastructure for the LHC project, which demanded very-large-scale data creation and transfer), the more advanced management systems necessary for Cloud computing and novel design approaches to SOA (Service-Orientated Architectures) design. More recently, Ed's focus has shifted to Cybersecurity (and network security in general), the challenges of autonomic control of distributed systems and the Internet of Things (IoT). Ed is currently an Associate Professor in Computer Science at the University of Southampton, affiliated to the Web and Internet Science group.