Beyond natives and immigrants: exploring types of net generation students

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Abstract
Previously assumed to be a homogenous and highly skilled group with respect to information and communications technology, the so-called Net Generation has instead been shown to possess a diverse range of technology skills and preferences. To better understand this diversity, we subjected data from 2096 students aged between 17 and 26 from three Australian universities to a cluster analysis. Through this analysis, we identified four distinct types of technology users: power users (14% of sample), ordinary users (27%), irregular users (14%) and basic users (45%). A series of exploratory chi-square analyses revealed significant associations between the different types of technology users and the university that students attended, their gender and age and whether the student was local or international. No associations were found for analyses related discipline area, socio-economic status or rurality of residence. The findings are discussed in light of the rhetoric associated with commentaries about the Net Generation, and suggestions about their implications for teaching and learning in universities are offered.

Keywords
Digital natives, net generation, technology, students.

Introduction
In the past decade, much of what has been written about the technology skills, preferences and experiences of current university students has conveyed an underlying assumption that today’s young people can all be characterized as ‘digital natives’. Also described as the ‘Net Generation’, they are generally assumed to be a homogenous group characterized by their wide experience and advanced skills in using information and communication technologies (Tapscott 1998, 2008; Prensky 2001a,b; Oblinger & Oblinger 2005). Until recently, what we know about digital native or Net Generation students has been largely derived from anecdotal accounts or based on untested assumptions [see Bennett et al. (2008) and Bennett & Maton (2010) for reviews].

For example, it has been widely assumed that current and recent university students have a greater interest in and aptitude for using digital technologies than their teachers and previous generations of students and that their familiarity with digital technologies has influenced their preferences and skills in key areas related to education (see Tapscott 1998, 2008). It is generally accepted, for instance, that Net Generation students demand instant access to information and expect technology to be an integral part of their educational experience (e.g. Prensky 2001a,b; Oblinger & Oblinger 2005; Barnes et al. 2007; Philip 2007). However, recent empirical evidence does not fully support these assumptions.

Empirical research into Net Generation students’ use of, and preferences for, technologies in higher education has begun to emerge in recent years (e.g. Conole et al. 2006; Ipsos MORI 2007; Oliver & Goerke 2007; Kennedy et al. 2008, 2009; Smith et al. 2009; Czerniewicz & Brown 2010; Jones & Healing, 2010; Jones
et al. 2010). In general, these studies reveal a level of technology adoption and use well below that predicted by the digital native/Net Generation rhetoric. It appears that while most students regularly use established technologies such as email and Web searching, only a small subset of students use more advanced or newer tools and technologies.

Much of what is known about students’ access to, and use of, technologies comes from an ongoing series of large-scale surveys conducted by the Educause Center for Applied Research (ECAR) in the USA [e.g. Smith et al. (2009)]. These surveys confirm that established technologies such as computers, the Internet and mobile phones are widely used by US college students. However, with the exception of social networking and instant messaging tools (Lenhart et al. 2007; Smith et al. 2009), most new and emerging technologies, including many under the Web 2.0 umbrella (e.g. podcasting, blogs, wikis and social bookmarking), are less widely used. Similar findings have been reported by Australian (Oliver & Goerke 2007; Kennedy et al. 2008, 2009) and UK (Jones et al. 2010) surveys of students’ use of emerging technologies.

There have also been a number of smaller in-depth qualitative investigations into Net Generation students’ perceptions of – and expectations for – the use of learning technologies in higher education (e.g. Conole et al. 2006; Ipsos MORI 2007; Lohnes & Kinzer 2007). These studies reveal that the relationship between Net Generation students, technologies and education may be more complex than commonly believed. Technologies are not always welcomed by students in learning settings. For instance, in Lohnes and Kinzer’s (2007) study, one student’s use of a laptop computer in class was seen as ‘antisocial’ by other students. The ECAR studies have consistently shown that a small majority of the students surveyed prefers only a ‘moderate’ amount of Information Technology in their courses (see Kvakik 2005; Salaway et al. 2007, 2008; Smith et al. 2009). Furthermore, students do not appear to widely embrace the knowledge-sharing and production capabilities of new and emerging technologies. For many students, learning technologies are seen primarily as tools for facilitating access to information resources rather than as communication tools that enable new forms of collaborative learning (Ipsos MORI 2007).

Much of this research has undermined the arguments underpinning the rhetoric surrounding digital natives and the Net Generation. Prensky (2001a) argued that all students were ‘“native speakers” of the digital language of computers, video games and the Internet’ (p. 1), whereas the evidence suggests a diversity of technology adoption and use within the current generation of students. Using relatively simple statistics such as frequency counts and mean scores, much of the quantitative research has indicated that the average student is not a sophisticated user of technology. However, few have considered the different types of technology users that make up the Net Generation. In other words, while previous research has clearly indicated that the Net Generation is a diverse rather than a homogenous group when it comes to use of and experiences with technology, few studies have directly and empirically attempted to uncover this heterogeneity. A key aim of this investigation therefore was to determine whether discernible types of technology users could be established from a large sample of students who were beginning their undergraduate studies at three Australian universities.

**Taxonomies of digital nativeness**

Prensky (2001a) originally described a dichotomy of digital natives and ‘digital immigrants’ that was based largely on age and technological experience. The concept of digital ‘nativeness’ quickly gained recognition and widespread adoption, partly because it had common sense appeal and could be easily verified by individuals’ experiences (see Bennett et al. 2008). Others have tried to categorize types of technology users based on empirical analyses.

As part of the Pew Internet and American Life Project, Horrigan (2007) sampled over 4000 American adults and asked them about their technological assets, their actions with, and attitudes towards technology. A cluster analysis was used with 3355 of the respondents to derive 10 types of technology users that included:

1. **Omnivores** (8% of the sample), who have the most information gadgets and services, which they use voraciously to participate in cyberspace and express themselves online and do a range of Web 2.0 activities.

2. **Lacklustre Veterans** (8%) are frequent users of the Internet and less avid about cell phones. They are not thrilled with Information and Communication Technology-enabled connectivity.
3 Connected but Hassled (10%) users have invested in a lot of technology, but they find the connectivity intrusive and the information burdensome.

4 Inexperienced Experimenters (8%) occasionally take advantage of interactivity, but if they had more experience, they might do more with ICTs.

5 Light but Satisfied (15%) use some technology, but it does not play a central role in their daily lives. They are satisfied with what ICTs do for them (adapted from Horrigan 2007, p. ii).

Classifying these groups more broadly, Horrigan (2007) suggested that 31% of American adults were elite technology users, 20% were middle-of-the-road users and 49% had few technology assets and technology played a peripheral role in their everyday life, if at all.

The motivation for the Pew Internet study was that ‘Little is known about which segments of the population are inclined to make robust use of information technology and which aren’t’ (p. I). While Horrigan’s (2007) investigation was of the general population, the motivation behind it is equally relevant to the higher education sector and students’ use of technology. Although Horrigan rarely mentioned students in his report, he did note that ‘two of the four tech-oriented groups have a higher-than-average percentage of members who are full or part-time students’ (p. 38).

Beyond age-based differences

As noted earlier, empirical research on the Net Generation has begun to emerge in recent years. Much of the empirical effort has focused on measuring students’ use of technology to determine whether it accords with popular commentaries in the area, primarily considering students’ general technology usage patterns (e.g. Conole et al. 2006; Ipsos MORI 2007; Oliver & Goerke 2007; Kennedy et al. 2008, 2009; Smith et al. 2009; Jones et al. 2010). Recent empirical studies have also considered how staff (Prensky’s digital immigrants) and students (his digital natives) compare with regard to technology use. This research suggests there is limited evidence of a clear distinction between digital natives and immigrants, although some differences have been identified (Kennedy et al. 2008; Waycott et al. 2010). However, given that a diversity of technology skills and experience is apparent within both the native and immigrant age groups, the value in classifying broad age-related characteristics is questionable. Research needs to move beyond identifying broad generational differences and examine other factors that may influence students’ use of technologies. Gaining a better understanding of the diversity within the student population in terms of technology use and the reasons for that diversity will allow us to develop a more sophisticated understanding of the role technology plays in the lives of different groups of students (see Bennett & Maton 2010; Jones & Healing 2010). This will contribute to more informed decisions being made when both traditional and emerging technologies are implemented as learning tools in universities.

Others have also begun to call for researchers to consider factors that may account for the variations in university students’ use of technology. For example, Bennett et al. (2008) suggested that some Net Generation research has ‘identified potential differences related to socio-economic status, cultural/ethnic background, gender and discipline specialisation, but these are yet to be comprehensively investigated’ (p. 778). Among the few such studies to date, UK-based studies by Jones and Ramanau (2009) and Jones et al. (2010) reported significant differences in technology use between students at smaller and more established universities but no differences in use according to gender. Smith et al. (2009) reported higher levels of technology use by male students, while Selwyn (2008) reported that females made greater academic use of the Internet than males. Selwyn also reported discipline-based differences, with students from medicine, social studies, law and business reporting higher use of the Internet for education than students from other disciplines. In an Australian context, Krause (2006) reported ‘surprisingly few differences between international and domestic students in their experiences with e-learning’ (p. 23), while in South Africa, Czerniewicz and Brown (2006) reported that international students had better access to, and aptitude for, technology.

These emerging research findings suggest that it is likely that demographic variables other than age – such as gender, socio-economic status, rurality and cultural background – impact on the degree to which Net Generation students adopt and use technology. Moreover, within the context of a national higher education system, it may be that differences between students are also associated with university-based variables (university type, discipline). It appears that there is the
potential for all of these factors to impact on technology adoption and use but to what degree and how they influence students’ use of technology requires further investigation. Given this, the aims of this investigation were twofold: to determine whether different types of technology users could be established in an undergraduate student sample and presuming such types could be identified, to ascertain whether they were associated with key demographic characteristics.

Method

Participants

The data presented in this paper are drawn from a comprehensive 2006 survey of first-year students’ use of technology conducted as part of a cross-institutional project investigating the Net Generation in the Australian Higher Education context (see Kennedy et al. 2006, 2009). Data were collected from 2588 students, and as we were particularly interested in Net Generation students, the sample for this investigation was restricted to those born after 1980 (i.e. aged between 17 and 26; \( N = 2096 \)) (McCrindle 2006).

Measures

The questionnaire administered to the students asked about the frequency with which they accessed and used technology-based tools, how they currently used technology to create and exchange information and knowledge, their skill levels with different technologies and their perceptions of how technologies could be used in their studies. The items presented for analysis in this paper relate only to those concerning the frequency with which technologies are used. The respondents could indicate the frequency with which they used 41 technologies or technology-based tools on an eight-point scale where ‘1’ was ‘not used’, ‘2’ was ‘once or twice a year’, ‘3’ was ‘every few months’, ‘4’ was ‘once or twice a month’, ‘5’ was ‘once a week’, ‘6’ was ‘several times a week’, ‘7’ was ‘once a day’ and ‘8’ was ‘several times a day’.

In addition to measures of technology use, the respondents were asked to supply a range of demographic and university-based information. Information was gathered on the university the students were attending, their age and gender, the course they were enrolled in, whether they were a domestic student or an international student completing higher education studies in Australia. The course that the students were studying was used to create a variable that broadly classified the students’ discipline as arts (22.5%), science (26.4%), professions (36.8%) or other (14.3%). This classification was based on categories defined by the Australian government department responsible for higher education. The domestic students were also asked to provide the national postcode of their permanent home address, which was used to create two further variables (socio-economic status and rurality) (Australian Bureau of Statistics 2006).

The three Australian universities involved in this study differ in their histories, their course profiles, the populations from which they draw their students and the volume of externally funded research which they undertake. The University of Melbourne is Australia’s second oldest university. It has a very strong research profile; its undergraduate population includes a large proportion of high-achieving students and its diverse course profile includes sought-after professional degrees including medicine and law. The University of Wollongong was established in 1975 and has its main campus in a large regional city. It has a developing research profile, offers a number of prestigious courses within its course profile and attracts an increasing proportion of high-achieving students. Charles Sturt University was formed in 1989 and is a multi-campus regional university. It has an emerging research profile and a significant proportion of its undergraduate population study part-time, at a distance and from less advantaged socio-economic backgrounds. Its course profile includes many professionally oriented courses including teaching and nursing.

Procedure

The survey was distributed through classes of first-year students across the three participating institutions in the second half of 2006. Data collection was carried out in accordance with the human ethics requirements of each institution, and participation was voluntary and confidential. More students from the University of Melbourne completed the survey (49.8% of the overall sample) than from the two other institutions (Wollongong: 28.8%; Charles Sturt: 21.5%) and more females than males responded (Females: 69.0%; Males 31.0%). There was a reasonable spread of age ranges in the
sample (17- to 18-year-olds: 19.1%; 19-year-olds: 43.7%; 20-year-olds: 18.1%; 21-year-olds: 7.5%; 22- to 26-year-olds: 11.5%) and a smaller number of international (13.9%) compared with local students (86.1%) participated. More students from major cities completed the survey (67.7%) compared with those from inner regional (25.7%) and outer regional or remote areas (6.6%), and there was a relatively even spread of students in the categories of low (34.6%), medium (31.8%) and high (33.6%) socio-economic status.

Results

The results are presented in two sections. The first section outlines how the data were prepared for analyses and describes the use of cluster analysis to identify categories of technology users. In the second section, these user categories are subjected to a series of exploratory chi-square analyses to determine whether they are associated with a series of key demographic variables.

Data preparation and cluster analysis

The students’ original responses to the questionnaire items using an eight-point scale were collapsed so that ‘0’ indicated ‘not used’, ‘1’ indicated ‘yearly’, ‘2’ indicated ‘monthly’, ‘3’ indicated ‘weekly’ and ‘4’ indicated ‘daily’. The items were then conceptually grouped into seven independent scales that described meaningful technology-based activities (some of the original items were excluded from the analyses at this stage as they did not clearly fit within a conceptual category). The seven scales, their definitions, means and internal reliabilities are reported in Table 1. The reliability coefficients for these scales were very good (ranging between 0.72 and 0.85), and in general, the students’ average use of most activities was relatively low (Table 1).

The students’ use of these seven scales was subjected to a cluster analysis in order to identify different types of technology users. Eighty-four participants were excluded from the cluster analysis because of incomplete or missing data. A hierarchical agglomerative clustering technique was employed using squared Euclidean distance as the proximity measure and Ward’s method as the clustering algorithm. Three-, four- and five-cluster solutions were specified.

The three-cluster solution clearly grouped the sample into low (N = 908), intermediate (N = 819) and high levels of technology use (N = 285). While this categorization was straightforward, the four- and five-cluster solutions captured additional details that were highly relevant to our analysis. The four-cluster solution is presented in Fig 1. In this solution, the low (cluster 1, N = 908) and high (cluster 4, N = 285) usage groups remained the same, while the intermediate group of users was split into two groups composed of those with lower (cluster 2, N = 276) and higher (cluster 3, N = 543) levels of technology use. Somewhat contrary to this trend, users in cluster 2 were more likely than their cluster 3 counterparts to engage in Web 2.0 publishing activities. The five-cluster solution was identical to the four-cluster solution except that a division in the lowest usage group created an additional, small, very

Table 1. Scales of technology based activities with definitions and descriptive statistics for usage.

<table>
<thead>
<tr>
<th>Scale</th>
<th>Definition</th>
<th>Mean (SD)</th>
<th>α</th>
</tr>
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<tbody>
<tr>
<td>Standard mobile use</td>
<td>Using a mobile phone to call and text people.</td>
<td>3.68 (0.69)</td>
<td>0.82</td>
</tr>
<tr>
<td>Standard Web use</td>
<td>Using the Internet to look up reference information for study purposes, to</td>
<td>2.68 (0.70)</td>
<td>0.72</td>
</tr>
<tr>
<td></td>
<td>browse for general information, to send or receive email, for instant</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>messaging, for commerce and services, and for other pastimes.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Creating and using</td>
<td>Using a computer to create, manage or manipulate digital images, for</td>
<td>1.65 (0.79)</td>
<td>0.80</td>
</tr>
<tr>
<td>media</td>
<td>creating presentations and for creating or editing audio and video files.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gaming</td>
<td>Using a computer, game console or the Internet to play computer games.</td>
<td>1.53 (1.08)</td>
<td>0.77</td>
</tr>
<tr>
<td>Advanced mobile use</td>
<td>Using a mobile phone as a personal organizer, to take and send pictures or</td>
<td>1.28 (1.03)</td>
<td>0.85</td>
</tr>
<tr>
<td></td>
<td>movies, listen to MP3s, make video calls, access the Internet, or to send</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>or receive email.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Media sharing</td>
<td>Downloading or sharing MP3 files or pod-casts, publishing pod-casts, sharing</td>
<td>1.11 (0.92)</td>
<td>0.74</td>
</tr>
<tr>
<td></td>
<td>photos or digital files on the Internet, using social bookmarking.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Web 2.0 publishing</td>
<td>Creating or commenting on blogs or vlogs, contributing to a wiki, and using</td>
<td>0.94 (1.09)</td>
<td>0.79</td>
</tr>
<tr>
<td></td>
<td>social networking software.</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
low-usage cluster ($N = 37$). This cluster was differentiated from the larger low-use group and all other clusters, based on mobile phone use. Whereas all other groups of users reported using mobile phones on an almost daily basis, this small group of users reported using mobile phones extremely infrequently. Given the low number of individuals in cluster 1 ($N = 37$), the four-cluster solution was adopted and subjected to further analysis.

A one-way Multivariate Analysis of Variance was used to determine whether the observed differences between the four clusters on the seven scales of technology-based activities shown in Fig 1 were significant. Given that the aim of cluster analysis is to derive groups that are clearly and statistically discriminated, it is not surprising that there were significant multivariate ($F(21, 602) = 204.78; P < 0.001$) and univariate effects for each of the seven scales. For the majority of the technology-based activities, the univariate tests described a pattern of use across the four clusters whereby cluster 4 > cluster 3 > cluster 2 > cluster 1. This was broadly the case for Advanced Mobile Use, Media Sharing, Creating and Using Media, Gaming and Standard Web Use. However, the cluster 2 users were significantly more likely to engage in Web 2.0 Publishing activities than their cluster 3 counterparts, and for Standard Mobile Use, the pattern of use was cluster 3 > 4 > 1 > 2.

Based on these results, we propose the recognition of four types of student technology users:

1. Power users (cluster 4): representing 14% of the sample, these students appropriate a wide range of technologies and use them significantly more frequently than all other users.

2. Ordinary users (cluster 3): representing 27% of the sample, these students are regular users of standard Web and mobile technologies particularly. While not averse to using emerging technologies and games, on average, they do so no more than monthly and tend not to engage in the Web 2.0 activities of Web publishing and file sharing.

3. Irregular users (cluster 2): representing 14% of the sample, these students are similar to the ordinary users, but engage in most of the technology-based activities less frequently. They are moderate users of standard Web and mobile technologies and relatively low users of all other technologies with the exception of Web 2.0 publishing.

4. Basic users (cluster 1): representing 45% of the sample, these students are characterized by extremely infrequent use of new and emerging technologies and less than weekly or monthly use of standard Web technologies. They are regular users of standard mobile features.

Fig 1 Frequency of technology use of the four-cluster solution.
Accounting for types of technology users

Having defined these user types, we sought to ascertain whether they were associated with seven key demographic variables, which were university, discipline area, gender, age, residency (international or local student), rurality and socio-economic status. A series of chi-squared analyses revealed significant effects for university, gender, age and residency but not for discipline, rurality or socio-economic status. Specific details about the significant results are reported in Tables 2–5.

The chi-square for university \[\chi^2(6) = 43.31; P < 0.001\] showed that students from the University of Melbourne were more likely to be Power and Irregular users and less likely to be Basic users than students from either the University of Wollongong or Charles Sturt University. University of Wollongong and Charles Sturt University students were both less likely to be Power users than University of Melbourne students. In addition, Wollongong students were more likely to be Basic users and Charles Sturt students were less likely to be Irregular users than students from other universities.

There were also clear gender differences \[\chi^2(3) = 53.84; P < 0.001\], which revealed that male students were more likely than female students to fall

Table 2. Chi-square analysis of association between university and type of technology user.

<table>
<thead>
<tr>
<th>University</th>
<th>Type of technology user</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Basic</td>
</tr>
<tr>
<td>Melbourne</td>
<td>Count (residual) 398 (-2.4*) 162 (2.2*) 259 (-0.6) 176 (3.0*)</td>
</tr>
<tr>
<td>Wollongong</td>
<td>Count (residual) 298 (2.2*) 72 (-0.9) 149 (-0.7) 64 (-2.0*)</td>
</tr>
<tr>
<td>Charles Sturt</td>
<td>Count (residual) 212 (1.2) 42 (-2.3*) 135 (1.7) 45 (-2.1*)</td>
</tr>
</tbody>
</table>

Table 3. Chi-square analysis of association between gender and type of technology user.

<table>
<thead>
<tr>
<th>Gender</th>
<th>Type of technology user</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Basic</td>
</tr>
<tr>
<td>Male</td>
<td>Count (residual) 246 (-2.1*) 53 (-3.5*) 198 (2.3*) 124 (3.9*)</td>
</tr>
<tr>
<td>Female</td>
<td>Count (residual) 662 (1.4) 223 (2.3*) 345 (-1.6) 159 (-2.6*)</td>
</tr>
</tbody>
</table>

Table 4. Chi-square analysis of association between residency and type of technology user.

<table>
<thead>
<tr>
<th>Residency</th>
<th>Type of technology user</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Basic</td>
</tr>
<tr>
<td>International</td>
<td>Count (residual) 60 (-5.8*) 76 (6.3*) 55 (-2.3*) 85 (7.3*)</td>
</tr>
<tr>
<td>Local</td>
<td>Count (residual) 847 (2.3*) 197 (-2.5*) 488 (0.9) 200 (-2.9*)</td>
</tr>
</tbody>
</table>

Table 5. Chi-square analysis of association between age and type of technology user.

<table>
<thead>
<tr>
<th>Age</th>
<th>Type of technology user</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Basic</td>
</tr>
<tr>
<td>17- to 18-year-olds</td>
<td>Count (residual) 165 (-0.6) 63 (1.4) 107 (0.4) 48 (-0.8)</td>
</tr>
<tr>
<td>19-year-olds</td>
<td>Count (residual) 410 (0.5) 134 (1.1) 222 (-1.1) 122 (-0.3)</td>
</tr>
<tr>
<td>20-year-olds</td>
<td>Count (residual) 155 (-0.6) 45 (-0.6) 95 (-0.2) 65 (2.0*)</td>
</tr>
<tr>
<td>21-year-olds</td>
<td>Count (residual) 70 (0.4) 15 (-1.2) 36 (-0.6) 26 (1.1)</td>
</tr>
<tr>
<td>22- to 26-year-olds</td>
<td>Count (residual) 108 (0.2) 19 (-2.3*) 83 (2.5*) 24 (-1.6)</td>
</tr>
</tbody>
</table>
into the two categories of higher technology users (Ordinary and Power users) and were less likely to be Basic or Irregular users. Conversely, female students were less likely than male students to be Power users and were more likely to be Irregular users.

The chi-square for residency \( \chi^2(3) = 152.77; P < 0.001 \) revealed that international students were more likely to be Power or Irregular users. The reverse was the case for local students, who were less likely to be in these categories. Local students were more likely to be Basic users than international students and international students were less likely to be Basic and Ordinary users.

The final significant chi-square analysis for age \[ \chi^2(12) = 28.08; P = 0.005 \] revealed an unexpected pattern of results, with few clear trends evident in the distribution of the data. Table 5 shows that 20-year-old students were more likely to be Power users than any other age category, while the oldest students (22- to 26-year-olds) were more likely to be Ordinary users and less likely to be Irregular users than any other age group.

Discussion

Prensky and others’ (e.g. Prensky 2001a; Oblinger & Oblinger 2005) claims about an emerging university population of digital native students being taught by a digital immigrant population of teachers led many commentators to suggest that major changes to school and university education would be required to accommodate their changing needs. Since then, a number of studies including our own (Kennedy, et al. 2007, 2008) and others (e.g. Salaway et al. 2007, 2008; Smith et al. 2009) have explored the characteristics of students and/or teachers in universities, resulting in a general acknowledgement that Prensky’s ideas were at best an oversimplification of the nature of staff and students’ use of technology. In particular, it is now well-established that the student population is far from homogeneous, with great diversity in access to, and frequency of, use of technologies. In this paper, we have explored this diversity, first by identifying different types of technology users within a Net Generation student group and second by looking at the degree to which these types of technology users are associated with various student characteristics.

Using cluster analysis, we identified four statistically robust types of student technology users: Power users (14%), Ordinary users (27%), Irregular users (14%) and Basic users (45%). Our ability to identify distinct types of technology users shows the utility of this type of analysis in gaining a more sophisticated understanding of Net Generation students’ use of technology. The analysis confirms previous research that suggests widespread diversity in students’ experiences with technology based on mean scores and frequency counts. Although the types of technology users that emerged from our analysis are different from the typology developed by Horrigan (2007), this is to be expected given the differences in sampling and methodology. This notwithstanding, there are clear analogies between at least two of our and Horrigan’s (2007) user types—his Omnivores and our Power users, and his Light but Satisfied group and our Basic users.

One of the key findings from the current study is that advanced technology users (our Power users) are in a minority, making up less than 15% of the students sampled. On the other hand, the largest group of students identified in our analyses, making up 45% of the sample, were rudimentary technology users (our Basic users), who used only standard Web-based applications and mobile phones on a relatively frequent basis. While the evidence suggests therefore that there is a clear subset of students who might fit with Prensky’s idea of ‘Digital Natives’, these students are the exception rather than the rule. The wide differences between the frequency with which Power and Basic users engaged in many technology-based activities (i.e. every couple of weeks versus yearly or not at all) highlights how within a single class at a university, there are likely to be major differences in students’ experiences and preferences in relation to technology.

The clear implication of these findings is that large-scale changes in curriculum or teaching approach based on assumptions about the technology experience of this generation of students as suggested, for example, by Prensky (2001a) and by Oblinger (2008) cannot be justified. This should not, however, be interpreted as an attempt to discourage the use of technology in teaching and learning. On the contrary, it is entirely appropriate to use technology in teaching and learning at university when this use is based on sound educational design principles that relate the affordances of a technology to intended learning outcomes. It is the use of technology
based on misguided assumptions about the technological experiences and educational expectations of students that should be discouraged.

While the relative differences in technology use of the four types of users were somewhat consistent across the seven technology-based activities, there were also clear variations between and within user types. For example, *Ordinary* users showed slightly higher frequency of use of mobile phones than *Power* users; *Irregular* users showed much lower use of gaming technologies than *Ordinary* users but very similar levels of sharing technologies, and *Irregular* users actually showed much higher use of Web 2.0 publishing technology than *Ordinary* users. Again, the overall diversity in the technological backgrounds of Net Generation students, coupled with the fact that the experiences of different student ‘types’ can vary with regard to specific technologies, has important implications for university educators, those who support them and policy-makers. For example, just because a student is a regular user of a social networking tool like Facebook does not mean he or she is a frequent or skilled user of media creation or editing applications. These are important findings for universities and their educators who, in relying on popular commentaries, may have made inferences about the generalized technology capabilities of their students. The existence of a large sub-population of Net Generation students with relatively little experience with many technologies demands that we pay careful attention to providing appropriate support and scaffolding to students when any other than the most basic technology-based learning activities are designed and implemented.

The second part of our analysis involved using a series of chi-square tests to determine the degree to which the four types of student technology users differed according to seven key demographic variables. There were significant differences between groups based on university, gender, age and residency, whereas there were no differences based on discipline, socio-economic status and rurality. Some of the key findings from these analyses were that the *Power* user group contained a higher representation of international students, students studying at the University of Melbourne, males and 20-year-olds, whereas the *Basic* user group contained a higher representation of local students and students from the University of Wollongong and contained a lower representation of students studying at the University of Melbourne, males and international students.

The analysis showed strong differences between the three Universities with the students from the University of Melbourne over-represented in *Power* users and under-represented in *Basic* users, and the students from Charles Sturt University and University of Wollongong under-represented in the *Power* users group. This is an interesting and perhaps surprising finding because it might have been expected that these institutional differences would reflect underlying differences between groups with regard to socio-economic status. However, this was not the case. The socio-economic status variable was created from the postcodes students entered on the survey in response to the question ‘if you are an Australian resident, what is the postcode of your permanent home address?’ It is possible that many students had moved away from their family home to attend university and regarded their new residence as their ‘permanent home address’, and consequently, postcode was not a reliable predictor of their socio-economic background. Alternatively, there may be other differences between students enrolling in the three universities (for example, levels of school academic achievement) that also correlate with frequency of use of technology.

There were very clear differences between the males and the females in their distribution between the user groups, with the males over-represented in the higher frequency user groups (*Power* and *Ordinary*) and the females over-represented in the lower frequency groups. However, the females were also over-represented in the *Irregular* group. Recent research has indicated that the females are more regular users of Web 2.0 social networking tools (Chan & McLoughlin 2008) and given relatively high use of Web 2.0 publishing partly distinguishes the *Irregular* user group; this may go some way in explaining why women were more likely to fall into this category. However, as mentioned in the introduction to this paper, recent empirical research considering gender differences in students’ use of technology has been somewhat equivocal (see Selwyn 2008; Jones & Ramanau 2009), and our findings add further uncertainty to this area. Clearly, more sophisticated explanations are required, which explore issues such as the possibility that males are more likely to be early adopters of technological tools (as suggested by Salaway et al. 2008) and that beyond this, males and females are more likely embrace distinct and different
technologies and tools (for example, games and social networking, respectively).

Clear differences between local and international students were evident, with international students substantially over-represented in the Power users group and the local students over-represented in the Basic users group. These results support Gray et al. (2010) findings that international students are more frequent technology users compared with local students. Moreover, the over-representation of international students in the Irregular users category – which is partly distinguished by relatively high use of Web 2.0 publishing – also accords with Gray et al.’s (2010) finding that international students were more likely to engage in blogging and social networking. These differences suggest that the students’ cultural background may play an important role in influencing their use of and experiences with technologies. Again, this has implications for tertiary educators as the increasingly globalized business of higher education needs to acknowledge and accommodate international diversity within student populations.

The results for age are somewhat surprising, in that one may have expected a greater proportion of younger students falling into groups that were high-technology users. Commentators have often used age as the defining variable for determining differences in students’ use of technology, and while the analysis in this paper considered a narrow age range of students, the lack of association between age and technology use suggests that age may be a comparatively weak factor when it comes to explaining variation in students’ use of technology. However, other research has revealed age-related differences in the use of social networking technologies. In the study by Jones and Ramanau (2009), respondents aged 20 and under used social networking websites more frequently than older respondents. This suggests that age differences may be more apparent when considering specific technology-based activities, particularly for technologies that support the social activities of young people.

The lack of discipline differences was somewhat surprising, particularly given they have been demonstrated previously (White & Liccardi 2006; Czerniewicz & Brown 2007; Selwyn 2008). It seems reasonable, for example, to expect that certain discipline areas would attract students with particular interest in, and experience with, technology. However, it is possible that the method we used to categorize the students into disciplines was too coarse. The surveyed students participated in a wide range of courses, which we grouped into three very broad discipline areas: science, arts and the professions. The professions group, for example, included students from discipline areas as diverse as engineering, education and medicine. Such groupings may not be fine-grained enough to capture discipline-specific differences in students’ technology use.

A further limitation of this paper is that the chi-square analyses were conducted separately for each demographic variable. Although this approach provided us with clear information about the ways in which types of student technology users varied with specific demographic variables, uneven distributions of students within the levels of different demographic variables can create difficulties with interpretation. For example, the gender and age distributions were not identical across the three universities, and consequently, it is possible that part of the university differences could be explained by gender or age differences. Readers interested in exploring this issue further are referred to our earlier papers that have used multivariate analysis of variance methods to look at the relative contributions of a range of independent variables in explaining the frequency of use of each category of technology (Kennedy et al. 2008, 2009).

In conclusion, three major findings can be drawn from this study. First, Net Generation students are far from homogeneous. Clear differences in their patterns of technology use can be established, allowing us to describe different types of users. Second, the individual technologies that any given student uses or has experience with one technology cannot be reliably used to predict experience with another. Third, there are a number of demographic variables other than age that may predict a student’s technology experience; these include gender, university and cultural background. Taken together, these findings provide further impetus to move beyond debates about ‘Natives’ and ‘Immigrants’ by seeking more sophisticated understandings of how students’ use of technology can impact on learning and teaching in higher education.

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Note

1Standardized residuals are reported in Tables 2–5. Cells with residual values greater than $\pm 2(*)$ indicate those that contribute to the overall significance of the chi-square test (see Watson et al. 1993).

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