What clever hominids browse: An empirical analysis of the relationship between web usage and academic performance in undergraduate students

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Abstract

The use of the internet, and in particular web browsing, offers many potential advantages for educational institutions as students have access to a wide range of information previously not available. However, there are potential negative effects due to factors such as time-wasting and asocial behaviour.

In this study, we conducted an empirical investigation of the academic performance and the web-usage pattern of 2153 undergraduate students. Data from university proxy logs allows us to examine usage patterns and we compared this data to the students' academic performance.

The results show that there is a small but significant (both statistically and educationally) association between heavier web browsing and poorer academic results (lower average mark, higher failure rates). In addition, among good students, the proportion of students who are relatively light users of the internet is significantly greater than would be expected by chance.

Keywords: internet usage, academic performance, study skills

Citation

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1. Introduction

The widespread availability of resources on the internet and their potential uses in educational settings has driven much debate in their use for teaching and learning. Students have easier access to a wider range of material, and can draw links between different information in new ways. However, the use of the web has been associated with negative behaviours and outcomes. Now that the internet has been used in universities for 15 years, and we have a generation of students who grew up with the internet, we are able to measure the impact and explore what type of web browsing behaviour is beneficial for students.

The internet has many different uses in a teaching and learning environment. We focus on the use of the world wide web – essentially the use of the http protocol – and investigate the association of academic

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2 The title of our paper is drawn from a 1982 paper in which Owen-Smith and Novellie [39] explored the foraging habits of Kudus and other ungulates. The choice of title is not just whimsical, as we use a technique from this paper to help analyse the internet usage of students.
performance and use of the web in a group of second year students at University of the Witwatersrand, Johannesburg (Wits). There have been a number of previous studies on this subject; however, they have relied on qualitative assessment of internet usage as well as self-reporting. These methodologies have a number of advantages, but they can only measure internet usage crudely. In our study, we have been able to draw on detailed proxy logs of student use of the internet. In particular, we can be sure that the logs we have for students who live in the University residences are a complete picture of the students’ internet usage.

The results of the study can be summarised as follows:

1. There is a small but significant – in both a statistical and educational sense – association between increased internet usage and poorer academic performance.
2. There is a distinct difference in usage patterns between good and weak students – the proportion of light users of the internet among good students is much higher than would be expected by chance.

We emphasise the use of the words “correlation” and “association” rather than “causality”. First, studies such as we have done can only show correlation, not causality. Second, even if there is causality — high internet usage causes poorer performance — it is likely that a deeper causality is more important: For example, depression is associated with both poorer academic performance [9] and higher internet usage [33]. Moreover, we cannot exclude that merely suppressing dysfunctional use of the internet would result in other dysfunctional behaviour. Thus, we see high internet usage as a symptom rather than the problem.

Structure of paper

We begin by discussing related research in Section 2. Section 3 presents the research methodology. Section 4 gives an overview of internet usage, which is followed by the key research results in Section 5. In Section 6, we briefly discuss other investigations that we performed. Finally, Section 7 discusses the results and conclusions.

The analysis of the results are too lengthy for full inclusion in this paper. We have selected some key results – the full results can be found in the appendix, as well as in an initial study done by Johnson [22].

2. Related work

The internet offers incredible access to resources for work, study and entertainment. Over the last 15 to 20 years much research has focussed on the use of the internet by various sectors of society. These papers have considered a range of subjects (adolescents, university students, disabled persons) and dealt factors like access, gender differences, social impacts etc. — see for example [18, 25, 47, 49, 17, 11, 52, 53] — and various authors have studied internet addiction or pathological Internet use in the general population, e.g., [56, 57, 2, 8, 31].

As mentioned above the resources of the Internet give enormous scope for a richer academic experience for students but also potentially offer a vast range of distractions which could impact negatively on the academic performance of both school and university students. A number of papers have focussed on the effect of Internet use on the academic performance of school children or adolescents (e.g. [20, 21, 28, 55, 41, 35, 14]).

General impact of internet use. Internet use (or abuse) by university students has been one focus of research. Some research focuses on general Internet use by students (e.g. [37] which looks at gender differences in Internet use and [26, 7] which both consider race/ethnicity differences). Some research considers how and/or why students use the Web/Internet. For example, Perry et al. [49] surveyed 548 students from 3 universities to see how many students regularly use the Internet, how many hours per week regular users spend on the Internet and what computers they use. They also asked respondents their views of their future use of the Internet in their future careers. Rumbough [44] investigated controversial uses of the Internet by university students (e.g. academic cheating, fake emails, pornography, etc.). Metzger et al. [30] found that college students report that they rely very heavily on the Web for general and academic information; that their use includes research (getting information) for school work, banking and stock market information, email, checking sports scores and downloading music; and that they believe that this use will increase over time).
Gordon et al. [16] investigated internet use and well-being among college students, with focus on frequency of use. This study aimed to determine what students use the internet for and how each of these affect their performance in college. A survey was performed on a representative sample of undergraduate students. This study identifies the top five types of internet use reported by students in the sample. The five types identified were: emailing friends, getting help with school work, talking with friends, emailing family, and instant messaging. These uses did not differ significantly between gender. Frequency of internet use was not found to be correlated with any of the well-being measures. It was found that the amount of time spent online was significantly associated with social anxiety, however this association became marginal after the types of use were entered into the model. The findings in this study suggest that the specific type of internet use relates to depression, social anxiety and family cohesion much more so than does frequency of use. It was also found that the internet has become an important aspect of college students’ lives. It was revealed that students mainly used the internet to email family and friends, IM, talk with friends, and get help with school work. This shows that students were drawn to the Internet primarily as a means of communication with friends and family. These results are similar to those found in previous studies. It was also found that men use the internet more for leisure, while women use the internet more often for communication. However, not much else was found in the way of gender differences. This shows that gender differences in patterns of internet use may be relatively small. The relationship between internet use and well-being is complex, what matters to a student’ well-being is not necessarily how long they spend online, but what they do online.

Fortson et al. [12] reported on internet use, abuse and dependence among students at a regional U.S. university. Once again a survey was used to gather information about the students in the sample. It was found that the majority of students use the internet daily, and that half of the sample met the defined criteria for internet abuse. There were no gender differences in terms of daily access to the internet, however males and females did seem to use the internet for different reasons. Finally, depression was found to be positively correlated with more frequent internet use [12].

A concern which is prevalent in the literature is whether “excessive” Internet use (also termed Internet addiction or pathological Internet use) could have a negative effect on the academic experience of university students. Some researchers report negative effects of Internet Addiction such as increasing time spent on line, disturbances of sleep patterns, isolation, etc. which could have an effect on academic performance but do not directly address the issue of academic performance (see for example Kandell [24], Chou and Hsiao [6], Morahan-Martin and Schumacher [32], Chou [5], Rotsztein [42], Fortson et al. [12], Odaci and Kalkan [36]).

Another area of research concentrates on the adoption of the Internet by institutions and focuses on appropriate adoption/use strategies and the effect of the adoption of the technology on the students’ university experience (see for example Jones [23], Matthews and Schrum [29], Hong et al. [19], Cheung and Huang [4], Salaam and Adegbore [45]). Some of this research specifically considers the effect of the adoption of the Internet on students’ academic performance. For example Osunade et al. [38] shows that there is a significant difference in academic performance between students at institutions that have Internet infrastructure and access on their campus and those that do not; and Tella [51] who studied the Internet usage of undergraduate students in Botswana shows that most of their respondents reported using the Internet for the purpose of obtaining course related information and that the Internet contributes significantly to their academic performance.

Academic performance. Kubey et al. [27] present the early findings of how internet use affects collegiate academic performance. This study focuses on students’ dependence on the internet and attempts to quantify to what extent students are addicted to the internet. It was found that a significant percentage of students whose academic performance was bad indicated that the internet kept them up late at night, thereby making them tired for lectures the following day [27]. Strong evidence was found to suggest that students’ excessive use of the internet is associated with academic problems, however it was unclear if these students would have had similar problems even without the internet being so readily available. These findings demonstrate the need for more research into this field, and specifically the need for hard data to be analysed, and compared to the self-reported data available from other surveys.

Wittwer and Senkbeil [55] explored whether a students’ computer use at home is related to their mathematical performance at school revealed some important results. The research aimed to determine if a
student using the internet at home would have a different mathematical performance in school than a student with no internet access. An important aspect of this research is that it compares the effects of home internet usage to other factors that have been identified as being important in prior studies. These factors include immigration background, leisure activities, cognitive abilities, how often they read books and newspapers, how often they watch television and the news, and how often they watch horror, action, or pornographic films. It was found that overall a student’s computer-related behaviour at home only plays a marginal role in predicting their academic performance. It was found that when compared to a student’s cognitive abilities, their immigration background, and leisure activities other than computer use, that a student’s access to a home computer did not contribute towards explaining differences in their mathematical performance. The frequency of computer use was also found to not contribute towards mathematical performance. However, other studies have found contradictory results, but measures taken in this research attempt to ensure the accuracy of these results. Finally, the only major computer related factor contributing towards students’ mathematical performance was found to be if the student was particularly interested in computers, and had acquired their computer skills themselves.

Other work more directly addresses the relationship between “high” Internet use and academic performance. Scherer [46] reports that 13% of the respondents in her study reported “excessive” Internet use that interfered with personal functioning. The study by Anderson [1] presents similar results for a small group of students (106 from a total sample of 1300 students from eight academic institutions) who used the Internet “excessively” – these students were significantly more likely to indicate that their Internet use negatively affected their academic performance, meeting new people and their sleep patterns. Suhail and Bargees [50] surveyed 200 undergraduate students in Pakistan and found that “excessive” Internet use can lead to many problems – educational, physical, psychological and interpersonal. Chen and Peng [3] surveyed a large sample of students in Taiwan and found that students who reported “heavy” Internet use were more likely to have worse academic grades, have worse relationships with the administrative staff, lower learning satisfaction and to be depressed, physically ill, lonely and introverted.

Frangos et al. [13] studied a sample of 1876 Greek university students in order to establish the degree of Internet addiction in these students. They applied a Greek version of Young’s Internet Addiction survey and added items on demographic factors and questions about academic performance. They found Internet Addicted students were more likely to report poor academic performance and that Internet Addiction was predicted by increased hours of daily Internet use; increased hours visiting chat rooms, sex pages and blogs; being male; being divorced; having poor grades; and accessing the Internet outside of the home. Englander and Terregrossa [10] found a negative and statistically significant correlation between time spent on line and the grade performance of 128 students in an introductory micro-economics course.

Social networking. A survey performed by Pierce and Vaca [41] to determine the differences in performance between teen users and non-users of social networking sites such as MySpace, as well as of other communication technologies, reveals some interesting results. The study made use of a survey which aimed to determine how many students report having a profile on a social network site, how many have cellphones, how many use text messaging, and in turn if the student uses each of these while doing homework, while in class, or during tests and exams. It was found that teen users of MySpace reported significantly lower grades than those who did not use the service. The same is true for teens with an instant messaging account, those with a cellphone, and those with text-messaging. A significant difference was found between students who had a MySpace account and those who did not – those who had a MySpace account reported significantly lower grades than those who did not have a MySpace account. A significant difference was also found between those who reported having an IM account, and those that did not. Finally, a significant difference was also found between those having a cell phone, and those without one. Those with cell phones reported significantly lower grades than those without one. Those who did have text-messaging on their cell phones also reported significantly lower marks than those who did not have text-messaging. It was also found that those who said they kept their MySpace open while doing homework reported significantly lower grades than those who did not keep their MySpace open while doing homework. The same was true for those who kept their IM account open while doing homework and those that did not. Those who text-messaged or who talked on their phones while doing homework also reported significantly lower grades than those that did not. It was also found that those who put off doing homework to spend time on MySpace reported significantly lower grades than those that did not put off their homework. While it is
not possible for the results of this study to reveal any causal link between grades and technology use, they do suggest that certain technologies can be very distracting to teens. This in turn can be linked to lower grades. It was also found that many students reported text messaging during class-time. This suggests that students are not paying as careful attention in class as they could be. Some students even reported text messaging during exams, this suggests that teens are using cell phones as a source of cheating which is highly disturbing.

Sources of data. A common theme of the research discussed above is that the data about Internet usage was collected by means of questionnaires or surveys administered to the subjects — i.e., the data used was self-reported. In the work of Jackson et al. [21] Internet usage (time online, number of sessions, domains visited and emails sent) was automatically collected for a period of 16 months. This data was then related to students’ grades. This research focussed on a fairly small group of low income high school students but the approach is similar to that which we adopted in our study. There has been no work reported that looks at hard data reflecting university students’ actual online behaviour and relating that to academic performance.

3. Methodology

This section discusses the data and how it was analysed. University of the Witwatersrand, Johannesburg (Wits) is a research university based (suppressed). There are approximately 18000 students in a first bachelor’s degree and about 6000 masters and doctoral students. There are five faculties: Science; Engineering & the Built Environment; Health Sciences; Commerce, Law & Management; and Humanities. The student population is very diverse, reflective of the region’s population (gender, race, and class). In particular some students had little or no exposure to computers and the internet before they came to University, while others have had computers since they were small children, with a good internet connection at home and in their high schools.

Sample of students. Second-year students were chosen as the focus of the study to reduce the heterogeneity of the sample. There were two reasons for doing this: (1) all students who pass the first year will have shown their ability to succeed at University and will have had some computing and internet experience, and (2) students at a more senior level may have significant discipline-specific internet usage requirements.

We were particularly interested in those students who were residing in university residences. Most importantly, it is a reasonable assumption to make that for these students there was no significant internet usage that was not captured by the proxies – the relative cost/performance of the university internet service for students (free, reasonable bandwidth) versus internet cafés and 3G services makes it unlikely students could use these services, and they would not have had significant access to DSL services. Another factor is that students in the undergraduate residences are much more homogeneous with respect to race and class than the general population.

Academic results. We selected a set of 11 second year courses across the University and used for our study all the students registered for these courses. This gives us a range of students in different disciplines and a sample in each discipline. We obtained all the marks for these students (not just the marks of the 11 courses) as well as the marks of other students to enable us to compute the average marks of any courses taken by the student sample. For each student we also recorded whether they were in a University residence. We excluded from the study all students who had obviously dropped out (marks of 0/failed absent).

Internet usage. We obtained the Squid proxy logs for all the students in the study for the second half of the academic year. In the 2007 academic year, the University had a strict policy which meant that all web browsing had to be done through an authenticating proxy. The log files were about 18.6 GB in size, with just over 105 million entries (URL requests).

Treatment of data. The data was anonymised in such a way that we could link academic performance and internet usage. It was then imported into a SQLite database – most of the analysis was done using SQL; however Python scripts were used for investigating the number of sessions. R was used for statistical analysis.
Categories of student. In the remainder of the paper we use the categories of the students based on their usage patterns as given below:

- Very heavy users: those in the top 10% of users by usage.
- Heavy users: those in percentiles 60-90% of users by usage.
- Light users: those in percentiles 10-40% of users by usage.
- Very light users: those in the bottom 10% of users by usage.

We study all four categories, though we focus on the heavy/light users rather than the very heavy/very light users since we are more interested in general effect rather than extremes.

Measurement of academic performance. Although we have hard data on student performance in courses, there is no completely accurate way to measure overall performance for a student since workload varies and different courses have markedly different averages. Ideally we would have one measure of student performance. However, there is no university determined index (such as a GPA).

For each student, we had all the courses done in the 2007 academic year. From this we computed the weighted average of the courses. Assuming a student did \( n_i \) courses, the weighted average is \( \sum_{j=1}^{n_i} p_i c_{i,j} / n_i \), where \( p_i \) is the weighting of the course and \( c_{i,j} \) is the mark the student \( i \) obtained for course \( j \).

From an initial analysis, we could see that internet usage varied across the different subjects as did the average mark for courses. For this reason, we also defined a performance index (PI) by relativising the mark the student obtained by the course average. This then gives a way of comparing students’ relative performance. Formally the performance index is \( \sum_{j=1}^{n_j} p_i (c_{i,j} - a_j) / \sum_{j=1}^{n_j} p_i \), where \( a_j \) is the average mark of all students in course \( j \).

The weighted average is the more obvious choice, but the performance index allows us to smooth out differences in standards (either of the students or marking). One problem with the performance index is that a student who does a course with relatively few students can have their PI unrealistically skewed up or down.

The average mark and performance index are both used in the analysis below because they both capture valid facets of academic performance. We also look at the proportion of courses passed.

Measuring internet usage. From the proxy logs, we must produce a usage index for each student. There are three ways this can be done. (1) Compute the total number of bytes downloaded; (2) Compute the number of URLs fetched – the number of hits – and (3) Compute the internet session time. Each of these have their advantages and disadvantages.

The student’s bandwidth utilisation may be misleading since it is conceivable that a student could write a simple script to download lots of music, which means they spend little time on the internet. The number of URLs visited by the student is misleading since most URL requests are as a result of indirect requests (one web page requesting others) and this measure may also be skewed by autorefresh. Measuring the number and length of sessions is difficult for a variety of reasons.

Students with no proxy records. In this study, we focus on students for whom we have both academic results and internet proxy results. However, approximately 28% of the students (610) had no proxy records at all. None of these students were in the university residence; hence, the most likely explanation is that these were students who had internet connectivity at home and no requirements for access at the University. The academic performance of these students was significantly better than the other students – an average 57.3%, and a performance index of +1.90. Since we find that lighter internet use is associated with better performance, excluding this noproxy group of students from the statistical study strengthens our conclusions.

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3 Across all students who did the course, not just students in the study. Thus the average performance index of all students in the study is not exactly 1.

4 The performance index (PI) gives us the difference in percentage points between a student and the hypothetical average student, who would have a PI of 0. The average PI of the students in the study is just less than 0, since the relativisation is done with respect to course averages, which included marks of students not covered in the study.

5 We applied the techniques used to measure animal behaviour in [39][48], and consulted the literature (e.g. [54]).
4. Overview of internet use

This section gives an overview of how students used the internet.

- Section 4.1 describes usage by number of bytes downloaded;
- Section 4.2 describes usage by number of URL requests (hits);
- Section 4.3 shows which sites were most popular;
- Section 4.4 characterises internet use by time of day; and
- Section 4.5 explores using number of sessions as a measurement.

4.1. Internet usage measured by download

Table 1 gives overall statistics of all the students chosen for the study. As should be expected students in residence use considerably more university internet resources than students not in residence. This should not be interpreted as saying that overall they use the internet more – it is just a statement about university resource usage.

| Category                                      | All students | Res students |
|-----------------------------------------------|--------------|--------------|
| Number of students selected for study         | 2153         | 557          |
| Number of selected with results               | 2147         | 533          |
| Number of selected with proxy data           | 1546         | 533          |
| Number with results and proxy data           | 1543         | 533          |
| Average proxy usage                           | 494 MB       | 773 MB       |
| Maximum proxy usage                           | 64 308 MB    | 64 308 MB    |
| Total download                                | 762 115 MB   | 412 164 MB   |
| Median proxy usage                            | 122 MB       | 217 MB       |
| Average number of hits (000)                  | 66.7         | 104          |
| Maximum number of hits (000)                  | 3185         | 3185         |

Table 1: Overview of students and data usage.

Table 2(a) gives a profile of how much downloading students do (as measured by number of bytes downloaded, including only those students who used the internet at least once. In summary, about two thirds used fewer than 250 MB, three quarters used fewer than 360 MB and just under 1% used more than 1 GB. The top 10% of users use 66% of total download; the top 20% use 81% of total download. For residence students, the usage figures are not as skewed but still the top 20% of users use 66% of download.

Table 2(b) shows the usage patterns of light and heavy users. For each percentile it shows the number of MB downloaded by those users. For example, the top 10% of all students (which we have characterised as very heavy users) downloaded at least 1001 MB and the top 20% of residence students downloaded at least 1338 MB. Similarly, among all students, heavy users downloaded between 175 MB and 1001 MB, light users downloaded between 5 MB and 72 MB, and very light users downloaded less than 5 MB over the period.

4.2. Internet usage measured by number of hits

This sub-section gives a similar overview of internet usage measuring the number of hits. Tables 3(a) and 3(b) show the internet usage by number of hits.
(a) Breakdown of usage – total download. Percentages are rounded to closest integer. The Usage column gives a range (in MB). All students shows the number and proportion of all students whose usage was in this range. Res students shows the same for students in the residence. For example, 9% of all students and 13% of residence students used between 200MB and 300MB.

| All students | Res students | Usage (range in MB) |
|--------------|--------------|---------------------|
| 716 (46%)    | 144 (27%)    | [0,100)             |
| 249 (16%)    | 102 (19%)    | [100,200)           |
| 135 (9%)     | 68 (13%)     | [200,300)           |
| 83 (5%)      | 42 (8%)      | [300,400)           |
| 60 (4%)      | 27 (5%)      | [400,500)           |
| 43 (3%)      | 24 (5%)      | [400,500)           |
| 39 (3%)      | 20 (4%)      | [600,700)           |
| 19 (1%)      | 9 (2%)       | [700,800)           |
| 24 (2%)      | 14 (3%)      | [800,900)           |
| 21 (1%)      | 11 (2%)      | [900,1000)          |
| 88 (6%)      | 40 (8%)      | [1000,2000)         |
| 31 (2%)      | 13 (2%)      | [2000,3000)         |
| 11 (1%)      | 5 (1%)       | [3000,4000)         |
| 6 (0%)       | 3 (1%)       | [4000,5000)         |
| 10 (1%)      | 6 (1%)       | [5000,10000)        |
| 8 (1%)       | 5 (1%)       | [10000,65000)       |

(b) Cut-off for percentiles. Entry for Percentile x shows that students in the top x% of internet users in the study used at least this amount of data in MB.

| Percentile | All students | Res students |
|------------|--------------|--------------|
| 10         | 1001         | 1338         |
| 20         | 482          | 701          |
| 30         | 285          | 475          |
| 40         | 175          | 312          |
| 50         | 122          | 221          |
| 60         | 72           | 160          |
| 70         | 39           | 120          |
| 80         | 16           | 74           |
| 90         | 5            | 33           |

Table 2: Overview of internet usage by bytes

(a) Internet usage measured by number of hits. This table shows what number of users made what number of hits. The range is shown in thousands. For example, 217 students made between 10000 and 19999 hits in the period.

| Range       | All students | Residence |
|-------------|--------------|-----------|
| [0,10)      | 573          | 105       |
| (10,20)     | 217          | 69        |
| (20,30)     | 128          | 57        |
| (30,40)     | 88           | 37        |
| (40,50)     | 85           | 36        |
| (50,60)     | 53           | 24        |
| (60,70)     | 46           | 23        |
| (70,80)     | 36           | 18        |
| (80,90)     | 31           | 10        |
| (90,99)     | 33           | 17        |
| (100,199)   | 144          | 81        |
| (200,300)   | 50           | 21        |
| (300,400)   | 25           | 15        |
| (400,500)   | 11           | 2         |
| (500,999)   | 19           | 12        |
| (1000,1999) | 4            | 2         |
| (2000,2999) | 4            | 3         |
| (3000,3999) | 1            | 1         |

(b) Cut-off for percentiles. Entry for Percentile x shows that students in the top x% of internet users made this number of hits.

| Percentile | All students | Residence students |
|------------|--------------|---------------------|
| 10         | 156          | 206                 |
| 20         | 82           | 125                 |
| 30         | 48           | 82                  |
| 40         | 31           | 58                  |
| 50         | 19           | 40                  |
| 60         | 12           | 26                  |
| 70         | 6            | 18                  |
| 80         | 3            | 10                  |
| 90         | 0.66         | 5                   |

Table 3: Internet usage by number of hits
4.3. Analysis of usage by URL

Note to reviewers: the details of some URLs is suppressed for double-blind reviewing.

The analysis of internet usage by URL downloaded is very instructive. Table 4 shows internet usage by URL, by number of hits. 140087 distinct organisational URLs were detected. The top 100 popular sites

| URL             | #hits | Perc. | Cum  |
|-----------------|-------|-------|------|
| studentvillage.co.za | 13258 | 14.51 | 14.5 |
| facebook.com    | 14750 | 14.03 | 28.5 |
| google.com      | 3011  | 2.86  | 3.67 |
| ying.com        | 2862  | 2.72  | 5.39 |
| yahoo.com       | 2730  | 2.60  | 8.0 |
| mtv.co.za       | 2381  | 2.26  | 10.3 |
| mig33.com       | 2175  | 2.07  | 12.1 |
| vodacom4me.co.za| 1976  | 1.88  | 14.0 |
| hi5.com         | 1222  | 1.16  | 15.1 |
| google.co.za    | 840   | 0.80  | 15.9 |
| wm.co.za        | 809   | 0.77  | 16.6 |
| google-analytics.com | 706 | 0.76 | 17.3 |
| slide.com       | 624   | 0.59  | 18.2 |
| careerjunction.co.za | 620 | 0.59 | 19.1 |
| webo.co.za      | 618   | 0.59  | 20.0 |
| live.com        | 592   | 0.56  | 20.7 |
| wits.ac.za      | 565   | 0.54  | 21.2 |
| standardbank.co.za | 529 | 0.50 | 21.7 |
| msn.com         | 528   | 0.50  | 22.2 |
| person.com      | 511   | 0.49  | 22.7 |
| thunda.com      | 504   | 0.48  | 23.1 |
| news24.com      | 491   | 0.47  | 23.5 |
| chat27.co.za    | 451   | 0.43  | 23.9 |
| akamui.net      | 429   | 0.41  | 24.3 |
| com.com         | 382   | 0.36  | 24.9 |
| iol.co.za       | 325   | 0.31  | 25.0 |
| bboybunker.com  | 312   | 0.30  | 25.3 |
| wikimedia.org   | 292   | 0.28  | 25.5 |
| myspace.com     | 271   | 0.26  | 25.7 |
| vodacom.co.za   | 261   | 0.25  | 26.0 |
| rockyou.com     | 258   | 0.25  | 26.5 |
| net.co.za       | 254   | 0.24  | 26.9 |
| bbc.co.uk       | 240   | 0.23  | 27.2 |
| myspacecdn.com  | 239   | 0.23  | 27.4 |
| go.com          | 239   | 0.23  | 27.7 |
| kaizerchiefs.com| 218   | 0.21  | 27.9 |
| images-amazon.com | 216 | 0.21 | 28.1 |
| premierleague.com | 206 | 0.20 | 28.3 |
| hotline.com     | 206   | 0.20  | 28.5 |
| standardbank.co.za | 206 | 0.20 | 28.7 |
| gumiire.co.za   | 198   | 0.19  | 29.0 |
| adbox.org       | 196   | 0.19  | 29.2 |
| supersport.co.za| 190   | 0.18  | 29.4 |
| adinterax.com   | 186   | 0.18  | 29.6 |
| uct.ac.za       | 185   | 0.18  | 29.8 |
| cupidbay.com    | 183   | 0.17  | 30.0 |
| oprah.com       | 174   | 0.17  | 30.2 |
| hideynlocation.com | 173 | 0.16 | 30.4 |
| userplane.com   | 172   | 0.16  | 30.6 |
| trendmicro.com  | 172   | 0.16  | 30.8 |

Table 4: Table of top 100 organisational URLs by number of hits. #hits is the number of hits in thousands. Perc gives the percentage of all hits go to this organisation. Cum gives the cumulative percentage.

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6To produce this table, we automatically stripped URLs so that we produced only organisational URLs – so only .edu or .nih.org – no sub-domains. We lose some information this way, but otherwise there are too many variations to make sense of the data. There is still some duplication, e.g. all .google sites, and some just given by IP address.
collectively account for 63% of all hits.

| URL                  | MB   | Perc | Cum  |
|----------------------|------|------|------|
| facebook.com         | 5783 | 7.46 | 7.5  |
| yahoom.com           | 3899 | 5.03 | 12.5 |
| yimg.com             | 2796 | 3.61 | 26.1 |
| myspace.com          | 2300 | 2.97 | 33.1 |
| google.com           | 1751 | 2.26 | 21.3 |
| studentvillage.co.za| 1156 | 1.49 | 22.8 |
| narutochaos.com      | 1010 | 1.30 | 24.1 |
| evilshre.com         | 9047 | 1.17 | 25.3 |
| hi5.com              | 8915 | 1.15 | 26.4 |
| symantec.com         | 8094 | 1.04 | 27.5 |
| url MB Perc Cum      |      |      |      |
|----------------------|------|------|------|
| 1 facebook.com       | 5783 | 7.46 | 7.5  |
| 2 yahoom.com         | 3899 | 5.03 | 12.5 |
| 3 yimg.com           | 2796 | 3.61 | 26.1 |
| 4 myspace.com        | 2300 | 2.97 | 33.1 |
| 5 google.com         | 1751 | 2.26 | 21.3 |
| 6 studentvillage.co.za| 1156 | 1.49 | 22.8 |
| 7 narutochaos.com    | 1010 | 1.30 | 24.1 |
| 8 evilshre.com       | 9047 | 1.17 | 25.3 |
| 9 hi5.com            | 8915 | 1.15 | 26.4 |
| 10 symantec.com      | 8094 | 1.04 | 27.5 |
| 11 url MB Perc Cum   |      |      |      |
| 1 facebook.com       | 5783 | 7.46 | 7.5  |
| 2 yahoom.com         | 3899 | 5.03 | 12.5 |
| 3 yimg.com           | 2796 | 3.61 | 26.1 |
| 4 myspace.com        | 2300 | 2.97 | 33.1 |
| 5 google.com         | 1751 | 2.26 | 21.3 |
| 6 studentvillage.co.za| 1156 | 1.49 | 22.8 |
| 7 narutochaos.com    | 1010 | 1.30 | 24.1 |
| 8 evilshre.com       | 9047 | 1.17 | 25.3 |
| 9 hi5.com            | 8915 | 1.15 | 26.4 |
| 10 symantec.com      | 8094 | 1.04 | 27.5 |

Table 5: Popular organisational web sites by download. The download figures are given in Megabytes. Perc gives the percentage of download from this organisation. Cum gives the cumulative percentage.

What is obvious from this is the dominance of social networking sites (the top 2 sites – almost 30% of usage are social networking sites), followed by sports. Google commands about 3.7% of all hits (this would be across all Google services). News sites (at positions 22, 26, 33, 70, 83) score highly but collectively command less than 2% of all hits. There are some sites for software download (Symantic and Adobe). Wikipedia and Wikimedia are at positions 28 and 59. Two university web sites also appear. Other than these latter two sites, no obviously academic sites appear. JSTOR appears at position 140, Springer at position 253. There are only two foreign universities in the top 1000. There is some web browsing that is...
academic in nature, and it may well be essential to the studies of the students involved, but as a statistical phenomenon, web browsing should be viewed as a social activity, just as participation in sports, student clubs or parties.

Table 5 shows the top 100 popular sites by download size. Overall the picture is similar, though some obvious software download sites (adobe.com, macromedia.com, caltech.edu) score highly. There may be some grey areas, and maybe some academics use Facebook for teaching activities but it is obvious that the vast bulk of internet download is used for social networking.

4.4. Internet use by time of day

Table 6 shows the use of internet by time of day. This is shown graphically in Figure 1. As would be expected, peak usage is around noon, but internet use remains high in the early evenings.

| Time | Number of hits |
|------|----------------|
| 0    | 1809726        |
| 1    | 1230086        |
| 2    | 923822         |
| 3    | 774641         |
| 4    | 1085260        |
| 5    | 2135939        |
| 6    | 3906422        |
| 7    | 4923858        |
| 8    | 5794114        |
| 9    | 6121647        |
| 10   | 6535347        |
| 11   | 6671627        |
| 12   | 6575327        |
| 13   | 7029927        |
| 14   | 6567500        |
| 15   | 6210050        |
| 16   | 4797886        |
| 17   | 5272394        |
| 18   | 5182216        |
| 19   | 5662758        |
| 20   | 5388305        |
| 21   | 4615795        |
| 22   | 3409579        |
| 23   | 2526842        |

Table 6: Internet use by time of day

4.5. Analysis of internet usage by sessions

Defining a session from proxy data is hard. A similar problem is tackled in zoology research – to define animal feeding sessions from observational data. See [39, 48] for a detailed discussion of some approaches. We applied the “broken stick” model of [48] which we now give a simplistic description.
When a foraging animal such as a Kudu eats, the gap between mouthfuls could either be an intra-meal or inter-meal gap. Both gaps can be modelled as Poisson processes: a fast one which describes gaps between mouthfuls in a meal, and a slow one which describes gaps between the last mouthful of one meal and the first of the next one. A simple technique for determining this is to compute log-frequencies of gaps, and then to plot the graph. In a pure one Poisson process model, the graph should be linear. In a pure two Poisson process model, the fast Poisson process will dominate the first part of the graph (small gaps) and the slow Poisson process will dominate the last part of the graph, and hence the graph should look like a “broken stick”: a steeply descending line at the left which at some point rapidly becomes a much shallower line towards the right. The break-point is then a good candidate for the gap between bouts. This break-point can either be found by eye or using the appropriate technique – see [48] for more details.

It is known that intra-session user behaviour is not Poisson, though inter-session is [54]. Nevertheless, we attempted a similar analysis with our data to see whether an obvious cut-off could be found. Figure 2 shows the histogram of gap lengths between individual users requests, binned into intervals of minute lengths. It is clear from this analysis that there is no obvious breakpoint. Experimenting with other distributions brought no insight.

This problem has been studied before and it is recognised as difficult [43] and the best estimates are a gap of about 15 minutes is reasonable [15, 34]. We adopt the same, and point out a serious methodological problem looking at the logs. Many web pages (such as popular web-based email systems and popular sports sites such as cricinfo and RSS feeds) have auto-refresh. Thus someone may not be using the internet at all, but the logs would still record them as doing so.

![Figure 2: Plot of log-frequency distributions between user requests](image)

5. Academic Performance and Internet Usage Results

In this section, we compare academic performance to internet usage. We primarily focus on internet usage as measured by number of bytes downloaded. We also did the analysis based on a measurement of

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We suspect that the high hit count for the BBC news site shown in our results is due to the fact that this site comes configured as a default RSS feed for Firefox. The peaks at the 30 minute and 60 minute mark may also be due to auto-refresh.
number of hits and got broadly similar results — for readability, the details of the analysis based on number of hits can be found in the appendix.

5.1. Heavy versus light users

Table 7 shows the performance of students in the various categories (e.g. heavy vs light; all vs residence students). On the whole, the table shows that the heavier users perform more poorly than the lighter users both with respect to average mark and performance index. As can be seen in Figure 3 the results are roughly bell shaped.

| Category      | All students | Residence students |
|---------------|--------------|--------------------|
| Very heavy    | 49.6%        | −4.21              |
| Heavy         | 52.1%        | −2.24              |
| Light         | 54.6%        | −0.54              |
| Very light    | 55.1%        | +0.07              |

Table 7: Academic Performance: Performance of students versus internet usage (bandwidth used). The figures in the table give the weighted average and performance index of the students in the different categories (e.g. heavy users in residence have an average of 51.6%).

We now do a detailed statistical comparison between light and heavy users. The descriptive statistics are shown below.

| Category  | All students | Residence students |
|-----------|--------------|--------------------|
| Light     | 54.63%       | −0.535             |
| Heavy     | 52.10%       | −2.241             |
| Light     | 54.42%       | −1.12              |
| Heavy     | 51.64%       | −1.53              |

We use the Wilcoxon rank sum test, the difference between heavy and light users is statistically significant with respect to average mark for all students and students in residence. The difference in performance index is statistically significant for all students but not for residence students. The difference between the statistical significance results for average and performance index is due to the latter smoothing out the difference in average marks between courses.

An analysis of academic performance versus number of hits yielded similar results – the details can be found in the appendix on page 22.

We looked at residence students in more detail and examined the difference between those students whose absolute use of the internet was between 50 MB and 150 MB; and those who used between 500 MB and 5000 MB (roughly equal groups). The average mark (PI) of the first group is 55.4% (−0.29) for the second group 51.6% (−2.43). The difference in average mark is highly statistically significant (p < 0.01), and the difference in performance index is significant (p < 0.05).

Thus, the results show that heavier users have poorer academic results than lighter users. There is some statistical evidence to support this. However, rather than using more statistical tests, we would rather focus on the question of whether there is a practical significant difference since 2% does not seem to be a big difference, especially in the face of confounding factors. We move to this question now.

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*One tail is probably OK to use here since we did hypothesise a priori that heavier users would have poorer performance.*
Distribution of marks

The difference of 1% may be trivial (13% or 14%; 67% or 68%) or huge (49% and 50%) i.e., the difference between passing and failing a course. This section analyses the performance of users based on the class of pass or fail. First, we look at the pass/fail issue.

| All students in the study | Very heavy users | Very light users |
|---------------------------|------------------|------------------|
| All results               | 9359             | 873              | 1096             | 100% | 100% |
| Number of passes          | 7242             | 258              | 903              | 77.3% | 70.6% | 83.4% |
| Number of fails           | 2117             | 615              | 193              | 22.6% | 29.4% | 17.6% |

| Students in residence     | Very heavy users | Very light users |
|---------------------------|------------------|------------------|
| All results               | 3136             | 285              | 299              | 100% | 100% |
| Number of passes          | 2386             | 217              | 211              | 75.9% | 71.1% | 76.2% |
| Number of fails           | 757              | 88               | 66               | 24.1% | 28.9% | 23.8% |

Table 8: Academic performance of very heavy and very light users – pass/fail outcomes in relation to bandwidth used across all courses (on average students register for 6.1 courses).

Table 8 shows the association of internet usage and passing or failing for very heavy and very light users. For each of the students in the study we looked at the number of courses passed and failed. We see that very heavy usage is associated with higher failure rates. Interestingly, among residence students, very light usage is associated with slightly higher failure rates than for light usage. We conjecture this is due to very light usage being related to the student effectively dropping out; for students not in residence, very light usage does not necessarily indicate they have dropped out since they may be using the internet at home. Table A.15 in the appendix shows the same thing by number of hits.

More interestingly, Table 9 shows the performance for heavy and light users. This also shows that heavier internet usage is associated with higher failure rates. A \( \chi^2 \)-test shows that this is highly significant \((p < 0.0001 \text{ for all students, } p = 0.034 \text{ for residence students})\).

Table 10 and Figure 3 take this analysis further and show that not only is internet usage associated with average pass/failure results of students but also between different average categories of pass. Table 11 shows the same result where we look at results across all courses (not just averaging over students). A similar result can be seen for the results by number of hits – see Table A.16.

The number of percentage points difference in the averages of the groups of students is small (2-3 percentage points), but as Tables 8 (very heavy versus very light users) and 9 (heavy versus light users), show this reflects in higher failure rates (a \( \chi^2 \) test shows that this is highly statistically significant). Not only does this make a difference in pass and failure rates, but also between classes of pass – fewer heavy users get good marks.

5.2. Internet usage versus academic performance

We are primarily interested in the effect of internet usage on academic performance but it is interesting to explore the patterns of usage of good and weak students.

First, we focus on the good students to see if their browsing habits are significantly different to the others. If we define “good” as an average of 65%, we see that 50.2% of good students are light or very light internet users (where if internet usage were not a factor we would expect 40% of the good students to be lighter users), and 27.1% of good students are heavy or very heavy users (a ratio of light-to-heavy users of 1.86 – by the way heavy and light users are defined, we would expect the ratio to be 1:1). Applying the \( \chi^2 \) test, we get a \( p \) value of 0.0026.

A similar result can be found with other cut-offs for “good” students: at 60% the ratio is 1.7:1, at 70% it is 2.23:1, at the 75% level 4.75 (at higher levels, the numbers do not allow statistical tests to be used, but no very heavy user of the internet had an average of more than 75%).

Table 12 gives another view of the results. The effect of a few massive downloads skews the results significantly and the number of “good” students is relatively small. We see, however, that over all students, good students (defined as those with an average at least 60) download less than weak students. On average
Figure 3: Histogram of results – (a) all students in the study, (b) residence students – see Table 10
good students download 266 MB while those with average 40% or less have an average download of 972 MB. Even if we exclude the really big downloaders who may skew the results we see the same pattern. If we exclude students with more than 10000 MB download the difference is 266 to 645 MB (and 266 to 512 for a 5000MB cutoff). Of course, as we exclude more students we lose information too – the cut-off of 5000 MB or 10000 MB is probably the fairest. For res students the situation is similar, good students download 448MB on average compared to 1659MB for weak students, and 448MB compared to 773MB for a 10000MB cutoff.

We performed an initial analysis of academic performance versus the number of sessions and total session length. The results are consistent with the analysis above – for example the very heavy users have an average mark of 50.4%, the very light users an average of 54%. The average mark of users in the top 40% of users is 51.5%, those in the bottom 40% have an average of 54.4%. In view of the consistency and the methodological problems discussed above in terms of measuring sessions we felt that further analysis would not shed more light.

6. Other investigations

We also conducted the following analyses, none of which showed meaningfully different results from the general results.

1. Does time matter? We had conjectured that students who did significant browsing at asocial hours (between 23:00 and 07:00) would be particularly prone to having poor academic results (either through being sleep deprived, or missing lectures to catch up sleep). We did an initial test to see whether time of day made a difference. We tabulated usage figures for those students who used the internet at asocial times (AU) (23:00-07:00) and got the results shown in Table 13. It is true that the people who were heavy asocial hours browsers had poorer results but the percentages were well in line with the results above.

Table 9: Academic performance of heavy and light users – pass/fail outcomes in relation to bandwidth used across all courses.

|                      | All students in the study |                      | Students in residence |
|----------------------|---------------------------|----------------------|-----------------------|
|                      | All results               | Heavy users          | Light users           |
|                      | All results               | Heavy users          | Light users           |
| All results          | 9359 100%                | 2828 100%            | 2816 100%             |
| Number of passes     | 7242 77.3%               | 2129 75.3%           | 2204 78.3%            |
| Number of fails      | 2204 22.6%               | 699 24.7%            | 612 21.7%             |

Table 10: Histogram of results based upon bandwidth usage. This histogram shows the distribution of average marks of students. A small difference in marks makes a larger difference in symbols.
### Table 11: Histogram of results based upon bandwidth usage. This histogram shows the distribution of marks across courses. A small difference in marks makes a larger difference in symbols.

| Mark range | All | Light | Heavy | All | Light | Heavy |
|------------|-----|-------|-------|-----|-------|-------|
| 0-9        | 287 | 87    | 87    | 88  | 18    | 38    |
| 10-19      | 59  | 26    | 15    | 19  | 6     | 5     |
| 20-29      | 172 | 63    | 60    | 59  | 15    | 21    |
| 30-39      | 686 | 190   | 218   | 259 | 76    | 80    |
| 40-49      | 913 | 246   | 319   | 325 | 93    | 107   |
| 50-59      | 3317| 891   | 1132  | 1211| 347   | 399   |
| 60-69      | 2641| 813   | 731   | 831 | 261   | 270   |
| 70-79      | 1000| 366   | 41    | 280 | 96    | 71    |
| 80-89      | 245 | 117   | 4     | 59  | 20    | 13    |
| 90-100     | 39  | 17    | 0     | 4   | 4     | 0     |

### Table 12: The entries in the table show usage in MB. The cut-off columns shows what happens if we exclude students who download more than the given cut-off figure. It is important to use some filter since otherwise a few very big downloaders skew the overall results. However, even at a cut-off of 5000MB we see that good students download substantially less than weak students.

| Category | Cut-off |
|----------|---------|
|          | None    | 10000  | 5000  | 2000  | 1000  |
| All students ≥ 60%: | 266    | 266    | 266   | 200   | 130   |
| All students ≤ 40%: | 972    | 645    | 512   | 287   | 186   |
| Res students ≥ 60%: | 448    | 448    | 448   | 316   | 197   |
| Res students ≤ 40%: | 1659   | 773    | 687   | 456   | 310   |

2. Does quality matter? The difficulty of studying the effect of what is downloaded is that there is such a wide variety of material that is downloaded. Since the top two sites (almost 30% of hits) were social networking sites, we investigated whether heavier users of these sites were particularly prone to poor marks. In doing this we picked the top two social networking sites taken from Table 4 ([facebook.com](http://facebook.com) and [studentvillage.co.za](http://studentvillage.co.za)). Collectively we call these SN users. Recall from Table 8 that the failure rate across all courses is 22.6%. The failure rate for SN users (any usage at all) is 22.9%, the failure rate for the top 20% of SN users was 25.3% and the failure rate for the top 10% of SN users is 30%. Again, the difference between heavy and light users was in line with the results above. This is understandable since even if we exclude the top two sites, the vast majority of sites are still non-academic. There are many different ways to waste your time.

3. Does Discipline make a difference? Do, for example, science students react differently to humanities students? Our initial study [22] indicated that there might be differences (for example the average marks of Economics students with high usage was higher than those of lighter users). However, when we did this initial study we only had partial marks for the students. When we had the complete results, although the exact differences in average marks of heavy and light users differed, there was almost always a negative association, even if small. From the internet usage profile it is also obvious that the difference in internet usage cannot be explained by the academic requirements of the different courses, though availability of computers and psychological profile might have an impact.

Students registered for an second year economics course 565 students. Heavy users have an average of 46.2% and light users have an average of 49.7%.

Students registered for an second year maths course. 771 students. Heavy users have an average of 55.3% and light users have an average of 58.0%.

Students registered for an second year maths course and not for a second year economics course 681 students. Heavy users have an average of 56.7% and light users have an average of 58.9%.

Students registered for an second year sociology, political science or anthropology and not for a second year economics course 385 students. Heavy users have an average of 55.52% and light users have an average of 55.14%. This was the one exception to the rule that heavy users perform worse
than light users

*Students registered for a second year law course but not economics* 949 students. Heavy users have an average of 52.7% and light users have an average of 55.5%.

### 7. Conclusion

The results of our study show the following:

- The vast majority of internet browsing by University students is non-academic in nature. The web is primarily a social space for students. This does not mean that the web does not have an academic role, and in some areas it is transformative. However, if we want it to be transformative, it is unlikely to happen by accident.

- Students with higher internet usage have a lower average than students with lower internet usage. The difference is small, but meaningful and statistically significant. This small difference in average marks is reflected in higher failure rates and fewer students with good marks.

- The internet usage of good students has a significantly different profile to that of weak students. Light users are disproportionately represented among good students.

What lessons can be drawn, and what further research should be done? We emphasise that with respect to the negative effect of internet browsing, these are more symptoms of underlying problems rather than primary causes.

There is a natural inclination on seeing results like these to apply measures to control access to certain web sites or classes of material for one of two reasons: (1) To prevent students from wasting their time and (2) To mitigate resource contention. While we have some sympathy with the second reason, the first reason seems to miss the point that there are underlying problems that should be tackled, and that even though heavy internet usage is associated with poorer marks, the difference is not that dramatic.

In our view the key issues are the following:

- An examination of the logs shows that a small group of students use the internet so much that it must be dysfunctional. This probably affects less than 5% of students and can only be dealt with through pastoral care of students, which is often not possible in a large university. Detecting the problems is also hard. While it is possible to give real-time feedback to residence officials, for examples, on internet usage, this is problematic when it comes to issues such as privacy.

- Time-planning and organisational skills. Improving students’ abilities to organise themselves and improve their self-discipline is independently desirable. Our results show that the internet is another possible trap for students. This issue should explicitly be raised with students, and we believe that our results will be instructive. It is particularly instructive to see the difference is browsing patterns of good and weak students.

There were a number of relevant issues that our work only tangentially dealt with. Future work should explore these. The ability to use the internet *effectively* is crucial. Often students (and staff) use the internet and tools such as search engines and bibliographic systems such as PubMed in the crude ways. There is a need to improve these skills, though it is best for this to be done in an integrated way. The use of the internet cannot be divorced from the general ability to read, synthesise, understand and write. Availability of the internet by itself does not help this – it may even have a negative effect. The question of e-learning, where material and software systems are explicitly used to support teaching is a separate issue.
Ethics clearance: This study was approved by the University of the Witwatersrand Human Subjects (Non-medical) Ethics Committee, protocol number H080618.

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Appendix A. Impact of number of hits made

Appendix A.1. Performance of students based on number of hits

This section presents compares the academic performance of students versus internet usage as measured by the number of hits.

| Category   | All Students | Residence Students |
|------------|--------------|---------------------|
| Very heavy | 49.1% −4.84  | 49.5% −4.53         |
| Heavy      | 51.8% −2.43  | 51.5% −2.75         |
| Light      | 55.2% −0.11  | 54.4% −1.48         |
| Very light | 55.5% +0.99  | 54.6% +0.92         |

Table A.14: Academic Performance Performance of students versus internet usage (number of hits). The figures in the table give the weighted average and performance index of the students.

Table A.14 – based on hits rather than bandwidth used – shows a similar trend to Table 7

Statistical test: All students average mark: Light users: 55.17/13.22. Heavy users 51.79/12.200. Using t-test and Wilcoxon highly statistically significant (p < 0.0001). Performance index: Light users: −0.114/12.7; heavy users −2.425/11.2. Statistical tests statistically significant (p = 0.003, 0.00086).

Residence students average mark: Light users: 54.40/11.20. Heavy users: 51.52/11.20. Using t-test and Wilcoxon significant (p = 0.022, p = 0.014). Performance index: Light users -1.476/10.432. Heavy users: −2.750/11.12. Not statistically significant (p = 0.29, 0.49).

Appendix A.2. Pass/fail rates versus internet usage – number of hits
### Table A.15: Academic performance of very heavy and very light users – pass/fail outcomes in relation to number of hits.

| All students in the study | All | Very heavy users | Very light users |
|---------------------------|-----|------------------|-----------------|
| All results               | 9359| 100%             | 918             | 100% |
| Number of passes          | 7242| 77.3%            | 657             | 70.9%|
| Number of fails           | 2117| 22.6%            | 267             | 29.1%|

| Students in residence     | All | Very heavy users | Very light users |
|---------------------------|-----|------------------|-----------------|
| All results               | 3136| 100%             | 318             | 100% |
| Number of passes          | 2386| 75.9%            | 227             | 71.4%|
| Number of fails           | 757 | 24.1%            | 91              | 28.6%|

Table A.16: Histogram of results based upon number of hits. This histogram shows the distribution of marks. A small difference in marks makes a larger difference in symbols.

| Mark range | All students | Res students |
|------------|--------------|--------------|
|            | All | Light | Heavy | All | Light | Heavy |
| 0-9        | 16 | 6     | 6     | 2  | 1     | 1     |
| 10-19      | 13 | 4     | 4     | 3  | 1     | 1     |
| 20-29      | 44 | 14    | 13    | 13 | 2     | 4     |
| 30-39      | 105| 25    | 36    | 35 | 10    | 12    |
| 40-49      | 289| 71    | 99    | 120| 36    | 41    |
| 50-59      | 610| 180   | 202   | 226| 59    | 70    |
| 60-69      | 379| 131   | 84    | 114| 42    | 21    |
| 70-79      | 79 | 37    | 16    | 18 | 5     | 7     |
| 80-89      | 6  | 5     | 1     | 1  | 1     | 0     |

Table A.16: Histogram of results based upon number of hits. This histogram shows the distribution of marks. A small difference in marks makes a larger difference in symbols.