Dealing with plagiarism in the digital age
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Introduction
The use of digital technologies has opened up a plethora of useful and credible information for use by students. However, this has also exposed the risks of uncritical and unacknowledged use of other people’s work. There is wide concern in the Higher Education sector that this has led to an increase in the incidence of plagiarism in Higher Education (Duggan, 2006; Evans, 2006; Hart & Friesner, 2004; Maurer, Kappe, & Zaka, 2006; Park, 2003).

There have been numerous cases of plagiarism in Higher Education discussed in the media. In the USA, 18 students left the University of Virginia after an in-house electronic detection system (Wcopyfind http://plagiarism.phys.virginia.edu/Wsoftware.html) led to the investigation of 158 students for plagiarism (D. Johnson, Patton, Bimber, Almeroth, & Michaels, 2004; Schemo, 2001; University of Virginia Honor Committee, 2000). In Australia a series of high-profile cases led to a “media frenzy on plagiarism issues” (Sutherland-Smith & Carr, 2005). In the UK, plagiarism in Higher Education never seems to be far from the headlines (BBC News, 2008; Hayes, 2009).

Institutions have met these concerns with a range of measures, including the widespread adoption of electronic detection systems (Culwin & Lancaster, 2000; Maurer et al., 2006). The situation has moved very quickly, from the introduction of the UK national license for Turnitin in 2002/3 to the present situation where this software is used by over 95% of Higher Education Institutions (Barrie, 2008) and is used worldwide by 10 million users in 100 countries (iParadigms, 2009). Safeassign, launched within Blackboard in 2007, processed 1 million papers in its first year of operation (Blackboard, 2008).

Given this explosion in use of tools to attempt to detect plagiarism by electronic means, this review surveys the literature for empirical research into the effectiveness, use and implementation of these tools.

As a relatively new area of research, the literature on the electronic detection of plagiarism is difficult to track down, as it is dispersed and often subject-specific. Commentaries, reports and research papers have been published in journals relating to the study of Higher Education, pedagogy, assessment, ethics and linguistics as well as in practitioner-based subject specific teaching journals. Therefore, to accompany this review, an online dynamic bibliography of the citations used has
been created on Citeulike (http://www.citeulike.org/group/11256). Citeulike is a social tool and as such any interested parties can contribute citations and recommendations as more work in this area is published, thereby keeping the bibliography up to date. It is hoped that this will provide an authoritative resource for future researchers, practitioners and policy makers.

**What is electronic detection of plagiarism?**

Plagiarism for the purposes of this review is taken to mean “The action or practice of taking someone else’s work, idea, etc., and passing it off as one’s own; literary theft.” (OED Online, 2009).

Authors have argued over the precise definition in the context of Higher Education (Jenson & De Castell, 2004; Warn, 2006). For this review, we refer separately to the concept of collusion, which refers to the practice of two or more students working together without acknowledgement. However, we acknowledge that collusion is a form of plagiarism. The distinction is made due to the fact that some electronic detection systems compare only student papers with one another, not with outside material, so some systems can detect only collusion or imply that two students have copied the same material from a third outside source.

The main subjects of this review ‘electronic detection software systems’ are the automated systems, which enable students’ work to be compared one with one another and with a variety of online sources. As has been pointed out elsewhere (Maurer et al., 2006) the ‘electronic detection of plagiarism’ is a misnomer, since none of the software systems available detect plagiarism per se, they simply detect non-original text (text that matches to another source). Non-original text is a flag for further investigation and may be entirely legitimate (for example: direct quotations, correctly cited; bibliographies). Academic judgment is required to make the decision about whether non-original text should be classed as plagiarism (Goddard & Rudzki, 2005; Mulcahy & Goodacre, 2004). ‘Electronic detection software system’ is, however, a convenient and descriptive term and one which we will use in this review.

**Effectiveness**

It is not within the scope of this desk-based literature review to test the various electronic detection of plagiarism systems available. The intention is to review investigations done by others and highlight the results, with particular focus on the evidence for the effects of using these systems on good academic practice by students. As the electronic detection of plagiarism is a relatively new technology, there has been a wide range of publications which review the tools available and report on preliminary tests of the systems (Briggs, 2008; Bull, Colins, Coughlin, & Sharp, 2000; Chester, 2001; Lancaster & Culwin, 2005; Maurer et al., 2006; McKeever, 2006; Purdy, 2005).

The effectiveness of these tools can be measured in two ways. Firstly, their accuracy in detecting non-original text in a piece of writing and secondly, in the effect they have on the actions of students in producing original and correctly cited work.

To consider the accuracy and utility of the electronic detection systems available, we
reviewed the studies that had performed comparative tests of multiple systems. Since this field has changed rapidly over the last ten years, many of the services tested in the past are now no longer in operation. The focus has therefore been on those currently available and functioning in 2009.

Only the use of free-text plagiarism detection software is considered in this review. A myriad of free, fee-based and subscription-based systems have proliferated over the years. While some have persisted many have fallen by the wayside. For example, McKeever (2006) reviewed a range of plagiarism detection systems and noted that five referred to, online and in the literature, were defunct at the time of writing and of the eight free-text systems reviewed, two were no longer available. A list of available systems is available online along with brief notes on their mode of operation (http://delicious.com/tag/electronic_detection+software).

There has been a limited number of empirical studies that have attempted to test the accuracy of electronic plagiarism detection systems. One the most influential was the study carried out by Bull (2000) (Bull et al., 2000) on behalf of the Joint Infrastructure Systems Committee (JISC). This was part of a four-strand approach to investigating plagiarism in Higher Education. Its outputs included the ‘good practice guide to plagiarism’ (Carroll & Appleton, 2001) which has become one of the most cited references in this area, a report on a pilot study of Turnitin (Chester, 2001) and a review of electronic plagiarism detection for source code (Culwin, MacLeod, & Lancaster, 2001).

Bull (2000) (Bull et al., 2000) reviewed five different systems, Turnitin (http://turnitin.com/), EVE (http://www.canexus.com/), Copycatch (http://cflsoftware.com/) Findsome and Wordcheck (Findsome and Wordcheck are no longer in operation in 2009). The review used 11 sample pieces to test each of the systems over a three-month period. Each system was rated on how effectively it discovered non-attributed text matches. It was noted that a direct comparison of all the services was problematic since they each operated on very different parameters. At the time of testing, Turnitin was the only product to offer checking for student-student collusion, copying from cheat essay sites and the Internet in one system. Although Copycatch was the highest rated product for accuracy of detection, this was only in the area of student-student collusion.

Published in 2005 from a study conducted in 2003, Purdy sought to compare the detection efficacy of two software systems, EduTie 1 and EVE2 (http://www.canexus.com/), against the search engine Google (www.google.com). Since academic staff had used search engines as a means of detecting plagiarism prior to their ability to access plagiarism detection software, Purdy reasoned that this last method warranted further investigation. He used five specially constructed test pieces and concluded that neither of the commercial systems performed appreciably

1 EduTie is now defunct but a forerunner of MyDropBox.com which has ultimately become Safeassign (http://wiki.safeassign.com/display/SAFE/About+SafeAssign), distributed by Blackboard (http://www.blackboard.com/)
better than Google. He expressed some concerns over the inconsistency of EVE2’s source detection. Other investigators have also rated Google highly in terms of accuracy of detection (Royce, 2003; Satterwhite & Gerein, 2001). None of these authors, however, consider the significant implications of the potential workload on academics that would be imposed by using Google as a detection method (Mottley, 2004). Indeed, several systems use Google or Microsoft Live Search as a detection mechanism and provide automatic processing of large numbers of student papers (e.g. Safeassign, OrCheck see:(Culwin & Lancaster, 2004). Open source and free of charge systems have long been a feature of electronic detection. Recently, (Butakov & Scherbinin, 2009) published an open source plagiarism detection plug-in for the VLE, Moodle which offers additional advantages to institutions, in developing nations with unreliable internet connections, by performing a mix of local and global searches.

Debora Weber-Wulff has undertaken extensive testing since 2004 and continues to repeat her tests on a regular basis. The analysis of each system considers its usability as a piece of software, and tests its efficacy to detect a variety of different types of plagiarism from a series of specially constructed test pieces. The test cases include completely original writing, material copied from Wikipedia, translations from other languages of publically available material, and an example of patch writing assembled from various unattributed sources. These are all written in German (for a published review of the software systems and methodology use in English see (Weber-Wulff, 2008). The most recent results from 2008 tested 16 systems. Points are awarded for the accuracy of detection for each piece of work, with a maximum of 80 points for complete detection of all sources from all the test cases. Interestingly the top two performing systems have not been widely reported for use in education. Copyscape (http://www.copyscape.com/) scoring (70/80) is designed to check the originality of web pages and as such is not a particularly practical option for checking student work which is most often submitted via a Virtual Learning Environment as a word processed document. Plagiarism Detector (http://www.plagiarism-detector.com/) scores highly (68/80) but there are doubts over its provenance since it carried a Trojan virus with its installation and the contact details for the company are misleading. Of the more commonly used plagiarism detection systems, Safeassign (57/80) scores above Turnitin (45/80). Turnitin scored in the mid range for accessibility and usability and only fully identified the sources of plagiarism for 8 of the 30 test pieces. In comparison, Safeassign found the original sources for 15 of the test pieces. The authors do note that Turnitin did not appear to cope well with the German language and that the database caused a high level of noise in the source matching.

Reports on the utility of electronic detection systems stressed the need for caution in interpretation of the results (Goddard & Rudzki, 2005; Mulcahy & Goodacre, 2004). It appears to have become accepted practice that non-originality reports provide only a guide for academic judgment in terms of the authority of the work tested (Atkinson & Yeoh, 2008). The limitations of the Turnitin database have been documented (Atkinson & Yeoh, 2008; Maurer et al., 2006; Warn, 2006), the main complaint being the lack of access to peer reviewed journals which are more commonly protected from open crawling by their publishers. However, Turnitin introduced searching of
some indexing and abstracting services in 2009 and the increasing amount of material becoming publically available online through open access repositories and projects such as Google books will begin to mitigate these deficiencies further.

Implementation

From the review of the utility of electronic detection of plagiarism systems, it is clear that although these tools may appear to provide an objective measure of plagiarism, in fact they offer evidence that must be subject to academic interpretation and judgment. The implementation of these tools in Higher Education therefore plays a key role in their effectiveness.

There is a large body of information on the uptake of these tools by institutions, including roll-outs, pilots, guidelines and the perceptions of staff and students to using these systems, much of it subject-specific (for examples see (Badge, Cann, & Scott, 2007; Chester, 2001; Evans, 2006; Mulcahy & Goodacre, 2004; Sheridan, Alany, & Brake, 2005; Whittle & Murdoch-Eaton, 2008)(Whittle & Murdoch-Eaton, 2008). We have not attempted to review all the pilot studies published since the majority simply restate and confirm the findings of others. We instead highlight some key or particularly influential papers. Since it is apparent from the publicized uptake of Turnitin and Safeassign alone that deployment of plagiarism detection software is now practically universal in the UK (iParadigms, 2009) the need for such pilot studies has passed. Best practice and adoption tend to be well ahead of the published research. As the field matures it is expected that the publication of pilot studies and implementation case studies will decrease and we will begin to see more work on the impact of electronic detection systems on longer term policies and practices.

Reports are now being made of institution-wide approaches to implementation of plagiarism detection software. One of the largest is the implementation of the electronic detection of plagiarism at the Open University. A leader in distance learning the Open University processes some 750,000 assignments every year. The university has worked closely with the developers of Copycatch to provide a custom solution for its courses (Heap & Woolls, 2006) that allows for comparisons to be made between student work and OU course materials as well as between student papers. The Open University is also using Turnitin and has recently overhauled its plagiarism policy (Open university's policy on plagiarism.2009).

Several studies have indicated that academics welcome the time saved by electronic detection in the investigation of individual cases of plagiarism. Advances in the integration of plagiarism detection systems into various virtual learning environments has helped to reduce the additional work by staff to upload and scan student assessments (Atkinson & Yeoh, 2008). However, it is acknowledge that since the commonly used detection tools only display matching text there has been a corresponding increase in the time they spend checking plagiarism reports in order to apply their academic judgment (Mulcahy & Goodacre, 2004: Sutherland-Smith & Carr, 2005). Staff often require training to be able to interpret the reports produced by plagiarism detection systems adequately (Atkinson & Yeoh, 2008; Goddard & Rudzki, 2005; Mulcahy & Goodacre, 2004). Lindsay (2003) argues that the conceptual difficulties of defining plagiarism will impact on our detection of it.
Policies on how to deal with plagiarism may not have been updated in the light of the use of Turnitin and so some staff are still put off from reporting plagiarism by the lengthy and unpleasant disciplinary procedures that ensue (Atkinson & Yeoh, 2008). In turn this can lead to staff not being particularly stringent in setting an adequate level of reporting in order to reduce their workload.

**Modes of Use**

We were also interested in studies where electronic plagiarism detection systems had been used with students to improve academic writing. Plagiarism detection has been used by instructors in a variety of ways in attempts to instruct and enlighten students on good citation practices and academic writing.

The proliferation of free web-based or downloadable systems for students to use to check their own work is perhaps inevitable in the current climate of detection by Higher Education institutions. This need has been recognised by iParadigms, who produce WriteCheck, a version of their own system, marketed at students. There is evidence that students are concerned about inadvertent plagiarism (Dahl, 2007; Martin, Stubbs, & Troop, 2006) and this is probably the driver for these sites. To date there is no discussion of student initiated self-check systems in the literature, though this is perhaps a natural area for future researchers to investigate. However, some instructors have focused on students accessing plagiarism detection reports generated by an institutional submission as a way to inform and educate their students in better writing and citation techniques.

Giving feedback about poor academic practice may be difficult for some staff. It has been reported that instructors may face considerable barriers when attempting to give feedback on plagiarism to students (Hyland, 2001). This may be because staff are uncomfortable with the acknowledged complexities of the line between paraphrasing and plagiarism or that they feel that their students come from a culture which has very different approaches to authorship and acknowledgement. This sub-text is most closely related to those dealing with overseas students or students where English is a second or third language.

Davis and Carroll describe a system where they have fed-back the results of non-originality detection on a short draft piece to their students without penalty or prejudice (Davis, 2007; Davis & Carroll, 2009). In this case the authors provided one to one feedback with students, reviewing the student’s non-originality report on their first draft together, looking at citation practices and paraphrasing. The students had an opportunity to then submit their full report in the light of this feedback. The results demonstrated a marked improvement in the final drafts, showing a measurable reduction in poor practices, including the amount of plagiarism, over-reliance on one source, citation errors and insufficient paraphrasing. Whilst impressive, these results were gained with small student groups (19-24 students per year) that could be given one to one support.

While the evidence for success with one to one support is important, many staff are not able to provide such a level of support. Other instructors have worked with much larger groups of undergraduates. Ledwith (2008) taught a class of 205 first year engineering students in Ireland, which already utilized peer review to ease the
burden of marking whilst providing students with individual feedback on their work. Of six summative peer-reviewed assignments, four were paper based and two submitted electronically. The electronic submissions were scanned by Turnitin for non-originality. Students were told of fixed penalties that would be applied to work above certain thresholds of non-originality and they were informed (as a group) of the generalized results of the detection software after their first electronic submission. The amount of non-original text detected in the second assignment was significantly less than in the first (Ledwith & Rasquez, 2008). In addition, ‘students rated their peer’s performance significantly lower when Turnitin was used to correct the assignments’ (ibid) suggesting that the use of this technology altered their perceptions of the standards of the work.

Two other studies report on the reduction of plagiarised text following resubmission of work by students. Firstly, Barrett and Malcolm (2006) observed a dramatic drop in non-originality detected on second submissions of postgraduate work from 26% of all submissions to just 3% of second drafts. There was an incentive for students not to repeat any plagiarism in a second draft, since those detected on the first round of submission had their marks capped at a bare pass prior to resubmission. Whilst the students undoubtedly reduced the amount of non-original material in their subsequent draft, there is no evidence provided on whether this was a learning experience for them and translated into better performance in other assignments.

Secondly, Lakomy (2004) showed third year students Turnitin originality reports from draft essay submission. They were given an opportunity to revise their work prior to the final submission. The students commented on the potential for the system to serve as a deterrent and to prevent ‘inadvertent’ plagiarism. However, several commented on the limitations of the service (at this point in time the main limitation was lack of coverage in the database of peer-reviewed subscription journals).

These studies involving single modules or classes of students leads us to question the longer term deterrent effects of plagiarism detection. Fintan Culwin has been active in the use of plagiarism detection tools in his own university over a number of years (Culwin & Lancaster, 2000; Culwin & Lancaster, 2001; Culwin & Lancaster, 2004; Culwin, 2006a; Culwin, 2006b; Lancaster & Culwin, 2005). In 2006 he reported that average percentage of non-originality detected in first year work over the previous four academic years had increased from 17.2% to 28%. He argues that this is due to the continual improvement in the databases and search methodology of plagiarism detection software and a corresponding improvement in the availability of online materials for students to use and techniques to discover it. In terms of progression through a student’s university career, he observed a reduction in the amount of detected non-originality between first and third year assignment (Culwin, 2006b). (Culwin & Lancaster, 2000; Culwin & Lancaster, 2001; Culwin & Lancaster, 2004; Culwin, 2006a; Culwin, 2006b; Culwin, 2006b; Lancaster & Culwin, 2005) However, the comparisons are not direct between the first and third years, as the plagiarism detection systems used for each were different (OrCheck and Turnitin respectively). In another study he found a correlation between the amount of non-originality and the likelihood of non-completion of the first year (Culwin, 2006a).

There is much discussion in the literature about the deterrent effects of a university
implementing plagiarism detection software (Bennett, 2005; D. Johnson et al., 2004; Sutherland-Smith & Carr, 2005). However, there has been little empirical work to demonstrate that this is the case. Since electronic detection is often the first objective measure of plagiarism that is applied across an institution, school or department there is often little base-line data on rates of plagiarism for comparison post-implementation. Indeed, these data may still not be available, as record keeping of cases involving plagiarism was found to be remarkably lax in the UK (Tennant & Duggan, 2008). Studies reporting the level of cheating or plagiarism in Higher Education most commonly use a self-reporting method, where students are asked to report on their own behavior (Franklyn-Stokes & Newstead, 1995; McCabe & Trevino, 1993; Szabo & Underwood, 2004). This can lead to unreliable subjective results.

To assess the deterrent effects of electronic detection systems, Woessner (2004) provides applies risk-benefit analysis to the relationship between penalties for plagiarism and the potential benefits to a student that plagiarises. He argues that resubmission of work for a lower grade does not provide a sufficient overall risk of a punitive outcome for a student considering academic dishonesty. In his scenarios, only failure of the complete course provides the potential sufficient impact on the student’s grades to make the behaviour too risky to attempt. It has been observed that students with poor time management skills or study skills (Franklyn-Stokes & Newstead, 1995; Newstead, Franklyn-Stokes, & Armstead, 1996; Underwood & Szabo, 2003) more likely to plagiarise text and unfortunately, Woesnner’s models show that penalties of any kind have a much greater cost to academically strong students than the weaker ones. The main assumption in Woessnner’s model that offers some hope is the perceived risk of detection by students. He sets this at a 3 in 4 chance of evading detection (ibid). This demonstrates how the need for detection to be consistent is balanced by the appropriateness of penalty.

Woessner concludes that unless the penalties and consequences of plagiarism are clearly spelled out for students, the potential of detection will offer no deterrent at all. This is borne out by Braumoeller and Gaine’s (2001) study that demonstrated no difference in amounts of plagiarism detected between two classes of political science students when one received stern verbal and written warnings concerning plagiarism and the potential penalties and the other had no warnings at all. In addition the problem of perceived potential for detection posed by Woessner’s model is also addressed by this study (Woessner, 2004). Braumoeller and Gaine (2001) publicised the effects of the non-originality detection software they had used (EVE http://www.canexus.com/ note: detects collusion only) on the grading curve for an assignment. Collusion detected for a subsequent assignment fell from around 1 in eight assignments to just one assignment across both classes (approx 90 students in each class). It was later discovered that the student submitting this piece of work had not heard about the detection software or its effects, adding further weight to the deterrent effect of the results of detection.

The important effect in Braumoeller’s work appears to the disclosure of the effects of plagiarism detection. Since these classes were norm referenced for marking, and any serious cases had 50% of their marks deducted, the effect of plagiarism could be easily communicated to a large group of students. Perversely, due to the way that
norm referencing works, this had the effect of raising the grades of the class. In spite of this, the public discussion of these results still had an effect on student behavior in the subsequent assignment and practically eliminated collusion. Further supporting this assumption, Ledwith (2008) included a qualitative survey of students that showed that they were impressed with Turnitin’s ability to find plagiarism. Students received information on the overall results of the detection system in a lecture but did not view the individual reports.

Other researchers investigating student and staff perceptions raise concerns about making the results of plagiarism software available to students. (Martin et al. 2006) surveyed students’ attitudes to plagiarism detection software. While the results showed that students overwhelmingly perceived the use of Turnitin as a deterrent and that it would discourage plagiarism, those that had actually viewed their own originality reports were less likely to believe that Turnitin would detect genuine plagiarism. In addition, this group were more worried about the use of Turnitin than those that had not seen the results for themselves. In a similar study of 24 postgraduate students that regularly used the Turnitin peer review tool to mark each other’s work and view their own originality reports, students agreed that they liked to see their originality reports (Dahl, 2007). However, when questioned further, the majority felt that they might be accused of plagiarism based on the originality report even though it was not true.

This highlights the concern that many staff have over the opening of the ‘black box’ of plagiarism detection software (Dahl, 2007). Some staff recognize that a reliance solely on electronic detection can lead to an arms race of detection and evasion. By making students aware of the detection protocols (D. Johnson et al., 2004), or the flaws in reliability of the rate detection (Lakomy & Price, 2004), they fear that they undermine the system and invite students only to think about beating detection and not good practice. Some staff believe that electronic detection should be used as a ‘purely punitive tool’ (Sutherland-Smith & Carr, 2005) and that a penalty for plagiarism would provide a learning experience which would stop those students from ‘re-offending’.

**Concluding remarks and future considerations**

Criticism of the searching mechanisms themselves, in particular that false positive and negative results can lead to the innocent being accused and the guilty going undetected (Braumoeller & Gaines, 2001; Royce, 2003; Warn, 2006) led to some questioning the validity of electronic detection. Hayes (2009) argues that the assumptions made about the particular paradigm required for learning in the UK, Australia and USA had led to electronic detection algorithms which disproportionately targets international students study in these countries. Jenson (2004) argued that imitation and appropriation are valuable tools for students to use in their learning processes and that the use of detection tools divert our attention from developing good academic practice in students.

Some feel that the efforts taken by academic staff to check the reports produced by electronic plagiarism detection tools may not be worth the cost of the false negatives slipping through the net (Evans, 2006). This raises the issue of whether academic staff time would be better spent on improving student writing and referencing skills
rather than on detection of non-originality after the fact. Many institutions have recognized the need to offer training to their students on plagiarism avoidance and that this needs to be available on a regular basis and not just in induction (Carroll, 2002; MacDonald & Carroll, 2006). Some institutions have incorporated quizzes in their online tutorials to provide active participation in the exercises (S. Johnson, Yakovchuk, & Badge, 2008). When the data is recorded from student attempts at such tutorials, it can be shown that student scores on the tests improve over time (Jackson, 2006). This could be taken one step further and linked to an institutional VLE in order to study a correlation between use of the tutorials, student degree results and even plagiarism detection reports. The Open University is one such institution already looking into this possibility (per comm. Arlene Hunter).

The widespread adoption of technologies to detect plagiarism in student writing has happened rapidly and there is still little solid empirical evidence to show the effectiveness of these tools in improving student practices. It has been argued that the introduction of these tools requires academic staff to make a radical shift in the way that teach students (Warn, 2006). Perhaps an area for future research could be the investigation of the impact on these tools on staff teaching practices. Have assessment practices begun to change? Staff can now be shown that their assignments can be answered by a single google query and repeated high levels of plagiarism on such assignments may force them to reflect on their own practices.

Ultimately, as was recognized by Carroll and Appleton (2001) long before the widespread adoption of electronic detection tools, no simple change in one element of practice will provide a long term solution to the problem of teaching our students how to be good scholars. The widespread adoption of electronic detection of plagiarism should be seen as only a first step in the effective dealing with plagiarism in a digital age.

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http://delicious.com/tag/electronic_detection+software

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