



Open Research Online

The Open University's repository of research publications and other research outputs

An embedded approach to plagiarism detection using the TeSLA e-authentication system

Conference or Workshop Item

How to cite:

Edwards, Chris; Whitelock, Denise; Brouns, Francis; Rodríguez, M. Elena; Okada, Alexandra; Baneres, David and Holmes, Wayne (2019). An embedded approach to plagiarism detection using the TeSLA e-authentication system. In: TEA 2018 Technology Enhanced Assessment Conference, 10-11 Dec 2018, Amsterdam, the Netherlands.

For guidance on citations see [FAQs](#).

© [not recorded]

Version: Accepted Manuscript

Link(s) to article on publisher's website:
<https://www.teaconference.org/>

Copyright and Moral Rights for the articles on this site are retained by the individual authors and/or other copyright owners. For more information on Open Research Online's data [policy](#) on reuse of materials please consult the policies page.

oro.open.ac.uk

An embedded approach to plagiarism detection using the TeSLA e-authentication system

Chris Edwards¹[0000-0002-0585-2697], Denise Whitelock¹[0000-0002-0585-2697],
Francis Brouns²[0000-0002-6240-2684], M. Elena Rodríguez²[0000-0002-8698-4615]
Alexandra Okada¹[0000-0003-1572-5605], David Baneres³[0000-0002-0380-1319],
Wayne Holmes¹[0000-0002-8352-1594]

¹ Open University (UK). Milton Keynes, UK

² Open University (NL). Heerlen, Netherlands

³ Universitat Oberta de Catalunya, Barcelona, Spain

Abstract. Plagiarism continues to remain an ever-present issue throughout academia. It is an anathema to scholarly enterprise, where the proper attribution of the work of others is of fundamental importance. Teaching students the importance of citing and referencing the work of others, and how to correctly do so, is therefore an important role for academic institutions. It is insufficient to teach these things without assessing students' learning. Effective and accessible tools that can assist in teaching and assessment are sought and are increasingly being developed.

This paper describes a new tool designed to assess levels of plagiarism in students' submitted work and considers its affordances alongside other established tools. TeSLA is an EU funded project that brings eighteen partners together for the development of an embedded suite of tools to deliver the seamless e-authentication of students as they complete online assessments. Within the suite is a plagiarism detection tool that analyses documents and text on submission and provides immediate output.

We show that the TeSLA plagiarism detection tool highlights potential collusion, a form of plagiarism. Also, we discuss whether the embedded nature of the TeSLA system could be used to improve constructive alignment between teaching and assessment within modules.

Keywords: plagiarism, constructive alignment, assessment, distance education, higher education, e-authentication

1 Introduction

Plagiarism is not going away and its presence undermines the scholarly process. It is an issue in the assessed work of students just as it is in papers written for formal publication. Institutions have a duty to teach students good scholarly practice and this should be visible through the learning outcomes of programmes of study. Universities themselves appear to have generally accepted assistance is needed in the identification of plagiarism in students' assessed work.

1.1 The need for assistance

As the cumulative volume of academic output increases rapidly, new technologies are required to manage databases and libraries. Microfiche records, familiar to many academics from their younger days have long since been usurped by computer records. In turn, these computer records have been transformed into large databases available anywhere through the internet. For example, the Educational Research Information Center (ERIC) database, ‘the largest education database in the world’ [1], is claimed to hold ‘over 1.5 million records of journal articles, research reports, curriculum and teaching guides, conference papers, dissertations and theses, and books’. The Web of Science platform states it holds data on ‘over 33,000 journals’ [2]. The increasing weight of original work makes it hard for most individuals to be familiar with more than the work associated with their specific narrow area of research interest. Whilst we may still be able to make a good judgement over the contribution a particular paper makes, this unfamiliarity specifically makes it harder to identify plagiarism and leads us, as teachers, to look for new tools that can assist. We have therefore essentially moved from a time when there was a reliance on the ‘informed reader’ [3] to identify plagiarism, to the time where potential plagiarism is highlighted for proficient academics to make a formal judgement. Woolls [3] emphasizes these plagiarism detection systems flag potential plagiarism and provide evidence, stopping short of deciding on guilt or innocence: a judgement that still needs to be made by an individual.

1.2 Types of plagiarism

Those reviewing papers and student assessments for considering plagiarism soon realise the term covers a range of types of plagiarism, from the completely copied work of someone else to a phrase without quotation marks. Woolls [3] lists three things that are needed for plagiarism to have taken place. We summarize them as:

1. Match – there is a match between the text in the document and some previously published work
2. Access – the author had access to the previously published work
3. Origin – the reader would presume these were the words of the author

From this list, we can see the source of some of the variety of types of plagiarism. The matching text may be a very small number of words – perhaps even one if it is an unusual word. The author may also properly cite the previous work elsewhere in their document but not indicate this quotation. It is hard however, to prove that the author did actually access the earlier work, and this is partly why a Chowdhury and Bhattacharyya define seven types of plagiarism [4]. Turnitin has produced its Plagiarism Spectrum [5], a document distilling their findings from a ‘worldwide survey of nearly 900 secondary and higher education instructors’. This has strong similarities with Chowdhury and Bhattacharyya’s list, and it is likely that alternative lists could be generated. Turnitin’s plagiarism spectrum describes ten different types and to each one

associates a level of severity and frequency of appearance. These are summarized in Table 1.

Table 1. Summary of Turnitin’s plagiarism spectrum [5]: Column S is the order of severity, with 1 the most severe; Column F gives the frequency of appearance, with 10 the highest.

S	Name	F	Description
1	Clone	9.5	Submitting another’s work, word-for-word, as one’s own
2	CTRL-C	8.9	Containing significant portions of text from a single source without alterations
3	Find-Replace	3.9	Changing key words and phrases but retaining the essential content of the source
4	Remix	5.6	Mixing paraphrased material from multiple sources
5	Recycle	5.5	Borrowing generously from one’s previous work without citation
6	Hybrid	0.5	Combining perfectly cited sources with copied passages without citation
7	Mashup	9.1	Mixing copied material from multiple sources
8	404 Error	0.6	Citing non-existent sources or including inaccurate information about sources
9	RSS Feed	2.8	Including proper citation of sources but containing almost no original work
10	Re-tweet	4.4	Including proper citation but relying too closely on the text’s original wording and/or structure

This list is useful as in practice we, as teachers, respond differently to the different items in this spectrum. Algorithms in plagiarism systems do not identify which form of plagiarism is being detected. Their outputs, with percentages of matching text and some with various coloured highlighting and supporting data enable us to readily make a judgement as to what is likely to have happened and how best to respond – remembering the goal is to assist others to learn how to write proficiently.

This paper presents a new system designed to assess levels of plagiarism in students’ submitted work. Trust-Based Authentication & Authorship e-Assessment Analysis (TeSLA) is an EU funded project that brings eighteen partners together for the development of an embedded suite of tools to deliver seamless e-authentication of students as they complete online assessments. Within the suite is a plagiarism detection tool that analyses the text in documents at the point of submission, providing immediate output.

This paper also considers this TeSLA tool against a set of various other established tools providing similar and different affordances. Our study does not focus on absolute values of efficacy of each plagiarism detection tool but rather on whether the TeSLA tool could be a viable tool to compliment others.

1.3 Plagiarism detection tools

There are many tools for identifying potential plagiarism, we have already mentioned a small number. An internet search reveals many more. Some of which are free for individuals to use. When there is such a large choice, detailed comparisons become

valuable in deciding which to use. The European Network for Academic Integrity (ENAI), with twenty-four member institutions and Co-funded by the EU's Erasmus+ programme, has as one of its nine stated objectives 'to provide a platform for academics across all sectors to investigate, exchange, develop, collaborate and access resources in the field of academic integrity' [6]. And this organization has attempted to make such a comparison. Their most recent report [7], published in 2013 attempted detailed testing of twenty-eight plagiarism detection systems, with fifteen systems completing the tests. Weber-Wolf et al, the report's authors, identify the presence of false negatives and positives showing that all the software systems cannot solely be relied on. They also use the term collusion to describe copying within a 'closed group of documents'. In these tests Urkund scored the highest accuracy with Turnitin joint second with Copyscape. The ENAI report also highlights the relative ease of use of the tools and this shows there is still considerable way to go before it is felt they are both effective and have sufficient ease of use.

At the Open University in the United Kingdom, OU(UK), two tools are routinely used to check the work that students submit: Turnitin [8] and CopyCatch [9]. Other partner institutions on the TeSLA project use different tools. For example, the Open University in the Netherlands, OU(NL), uses SafeAssign [10] and at the Open University of Catalunya, UOC, in Spain, where they use Urkund [11] for some courses.

The OU(UK) uses each of the two tools for a specific use. Turnitin is used to identify the potential plagiarism of already published material accessible using the internet. It checks the originality of the work. CopyCatch, on the other hand, is used to identify similarities between the work of OU(UK) students either within the same group, or more widely: as defined by the particular module team. To differentiate between the two uses, the latter is called collusion. Table 2 describes the affordances of the tools used by these institutions.

Table 2. Summary of affordances of the five plagiarism detection tools used in the study.

CopyCatch	Checks against selected groups of students' assessed work as required. And against any group of predefined texts. Is able to ignore text matches e.g. question text.
accepts:	OU systems convert documents to plain text for submission.
reporting:	Summary report on all pairs and returns full 'similarity'[12] report on highest matches for scrutiny, with highlighted text
SafeAssign	Checks against other students though not used in these courses, academic journals and the internet.
accepts:	.doc, .docx, .pdf, .txt, .rtf, .html, .htm, html, .wps, .odt, .zip
reporting:	Summary and detailed reports.

TeSLA	Checks against assessments received so far for one group.
verification:	Recalculates for all documents on each new submission. Is able to overlook text e.g. text from the original question.
accepts:	pdf, doc, txt. Including compressed.
reporting:	Maintains a database of all matches. By default returns highest match. Provides highlighted text for pairs of documents.
Turnitin	Checks against previously published work on the web.
verification:	
accepts:	.html, .doc, .docx, .hwp, odt, .rtf, .txt, .wpd, .ps, files from Google Drive, .pdf, ppt, pptx, .ppsx, .pps, .xls, .xlsx
reporting:	Produces a detailed 'originality'[12] report per document.
Urkund	Checks against three source areas: archives containing sources from the wider Internet, academically published material, and previously submitted student documents.
verification	
accepts	.doc, .docx, .xls, .xlsx, .sxw, .ppt, .pptx, .pdf, .txt, .rtf, .html, .htm, .wps, .odt, .pages
reporting	Provides an overview of the analysis with all the information needed for a teacher to judge if plagiarism has occurred.

Turnitin and CopyCatch make complimentary checks. CopyCatch is able to be adjusted by each module team. For some it might be important to check against all the work ever submitted for modules in that subject area. For other modules it may only be necessary to check against other work submitted in that particular assessment. In either case, CopyCatch is used to make the checks once the submission date has passed, and all work is in.

The TeSLA tool is invoked as a student submits their work and makes its checks against whatever work has already been received on a particular assessment. It is not possible therefore, for the person who submits the first piece to be flagged for plagiarism, as the tool will always return a value of zero. However, all submitted work is checked against every subsequent submission. Therefore, whilst the initial value for the first work to be submitted will be zero, this may change as more work is submitted by students.

1.4 Constructive alignment

A little over twenty years ago Biggs formed the notion of constructive alignment between teaching and assessment [13]. This has been very useful for many, as a guide for those devising programmes of study, preparing teaching and assessment materials and those involved with teaching. Biggs more recently explains how the concept is still relevant in 2014 [14]. He states that 'CA properly implemented enhances teaching and learning quality'. Stated very simply, the key steps are: to state clearly what it is intended students should learn; to provide learning activities/experiences that enable students to achieve these; to determine achievement through assessment. If we were to

consider how we fulfil these steps in terms of developing graduates who have sufficiently developed practice so as not to plagiarise within our own institutions, we might be surprised that perhaps there are gaps in our provision. For example, a learning outcome might be ‘To produce a scholarly report’. The activities and experiences that enable students to achieve this might include a general guide to academic writing, and the production of one or more reports as assessment. These are then marked as if they were papers submitted to an academic journal, with some students finding at this point that they are being accused of plagiarism. One way in which the OU(UK) has started to try to improve on this is to use a tool, jointly developed by OU colleagues, called OpenEssayist [15, 16]. This is an online system that provides detailed feedback with the option of this being graphically represented and can assist students with the structure of their writing and in the development of themes. We will consider later in this paper how TeSLA may also contribute to the development of student’s writing.

2 The TeSLA approach

TeSLA was conceived to provide a suite of e-authentication tools for students completing online assessment [17]. The tools were to be embedded within the virtual learning environment (VLE) of a university, so they could be invoked seamlessly as needed and in any combination. The tools included so far within the TeSLA system are facial recognition, forensic analysis, keystroke dynamics, plagiarism detection and voice recognition. The system has now undergone three phases of testing with students in real learning environments. This paper is focused on the findings from the use of the plagiarism detection tool and describes findings from three of the partner universities within TeSLA: the OU(NL), OU(UK) and UOC.

Table 3 summarises the number of students and tools used in each of the three case studies and the following sections detail their results.

Table 3. Summary of course and participant numbers, and tools used

University	number of courses	Number of students providing data	Tools used
OUNL	10	140	SafeAssign, TeSLA, Urkund
OUUK	11	185	CopyCatch, TeSLA, Turnitin
UOC	8	1332	TeSLA, Urkund

3 OU (UK) results

OU(UK) students were not required to participate in any of the TeLSA studies, in accordance with institutional practice. Participation has been made on a voluntary basis in the TeSLA pilots, members of staff were invited to include similar essays created only for tests. In total, the TeSLA study yielded 185 sets of CopyCatch, TeSLA and Turnitin values.

The values from each tool are not to the same scale. Turnitin reports percentage similarity and the TeSLA tool returns a text overlap value between 0 and 1, which we convert to percentage for comparison. The two tools use different algorithms and have different purposes. We would therefore not expect completely identical results but instead would expect some degree of similarity.

This trial involved some 13,227 students studying on one of 11 different modules, across a range of subjects, and at different levels. All these students were studying at a distance with their learning materials, assessment, collaboration, and communication with teachers and with other students all mediated through the internet. A separate TeSLA mini module was created for each of the tools included in the study (face recognition, keystroke dynamics, plagiarism detection at the OU(UK) in a parallel VLE to the University's main Moodle offering. This underlined in students' minds that this was an optional research activity that would not impact on their studies.

Students were selected through the university's prescribed procedures and then each was sent an invitation through the standard email system. Those responding positively to the invitation, agreeing to participate in the study would follow the link to the parallel Moodle VLE, where they would complete an initial questionnaire, carry out the activity that invoked the TeSLA tool, and then complete a final questionnaire. For the plagiarism detection tool, this required uploading an assessment that had already been submitted electronically through the university's system and marked. Not all modules use Turnitin, as this decision is made by individual module teams. Therefore, all submitted documents were passed to Turnitin and these results were compared with the output from the TeSLA plagiarism detection tool.

Turnitin results

It should be stated that the document falling in the highest bin in the histogram shown in Fig. 1, 91.8% to 97.2% was not a student's work but a deliberately plagiarized document included by the research team. This figure plots the frequencies of values within each of the ranges, and shows a sharp drop off, with only one document including between 21.6% and 27% similar text to other previously published work. In general terms, the individual charged with checking and acting on these results would start by looking at the detailed results of the document with the highest value. Once an initial determination as to whether this represents one of the forms of plagiarism was made, the next highest script would be examined, and so on until the academic was confident there was minimal likelihood of Turnitin identifying any form of plagiarism. In this way, submissions the academic considers do include plagiarism are identified and appropriately followed up. Also, false positives, where the results suggest plagiarism has taken place but that on investigation, none has, are discounted. This process does not deal with false negatives, where plagiarism has taken place but has not been identified by Turnitin. The extent of false negatives is therefore unknown. In fact, the handling of false negatives deserves its own discussion and is an issue none of these tools help with.

Fig. 1. Turnitin results from OU(UK), showing the spread of the percentages of similarity between text in each of the submitted documents and work already published.

TeSLA results

Of the 185 values plotted in the histogram in Fig. 2, 170 are zero. The highest TeSLA tool value was 0.16, of which there were three. These values, when converted to percentages, are markedly lower than the Turnitin results and are likely due to comparisons being made over such a small number of documents. The deliberately plagiarized piece of work does not stand out in these results: in fact, it received a zero score. We learned there had been a communication issue between the Moodle plug-in and the TeSLA server. Also, that this would return a zero for any file that had not properly transferred to the TeSLA server. Several students did report some technical issues and this seems the likely cause of a number of them. With the distributed nature of students and the wide variation in the hardware and software used, the resource required to find the true nature of any of these issues beyond any we had available.

Fig. 2. TeSLA results showing the spread of the values returned at OU(UK) from TeSLA for each of the submitted documents

CopyCatch results

CopyCatch was set up to give a detailed similarity[12] report for the maximum of the ninety-nine highest matching pairs of documents. It also provided an overall summary by listing the frequency of every percentage match. The following plot in Fig. 3 is of these frequencies. Although there were only 185 documents, CopyCatch examined almost twenty-five thousand pairs. It shows high numbers of pairs with low matches. Far lower than would normally trigger any scrutiny from the person examining the output. The documents providing the three highest values were checked and they were from students on the same course

Although all these 185 documents had been submitted by participating students to the TeSLA plagiarism detection tool through the study's website, we found that very few were successfully uploaded and the combination of this and the limit on the number of detailed reports available from the CopyCatch system means we are unable to make a meaningful correlation between the two tools. This is one of the unfortunate potential outcomes of a research study.

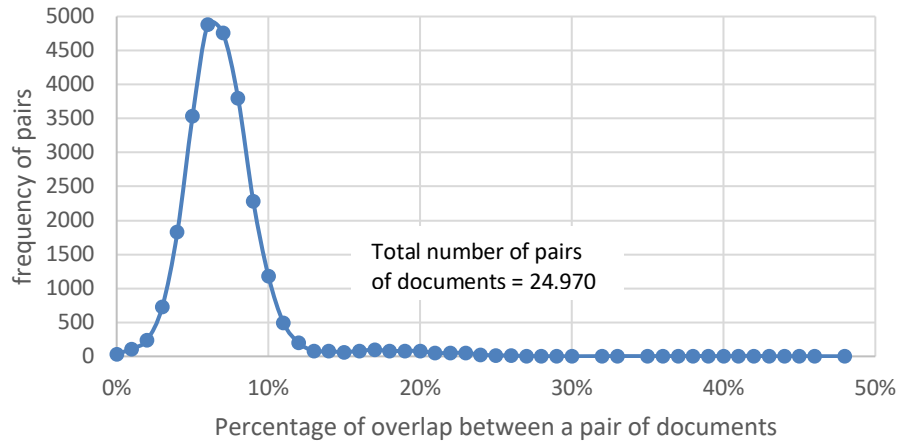


Fig. 3. Results from CopyCatch for OU(UK)

Note that with almost 25,000 pairs this is not a small dataset, even if there are only 185 students. There is a gaussian distribution centred around very low value. This is because students came from eleven different modules. However, the top scoring values, 48% and two at 46%, were checked and the three students submitted work for the same assessment.

4 OU(NL) results

The OU in the Netherlands also built a separate VLE for students to access the TeSLA tools. All the documents students participating in the study uploaded to the TeSLA plagiarism detection tool were also presented both to SafeAssign and to Urkund. OU(NL) were successful in obtaining results for all the potential document matches. The highest percentage match for each student was collected and these values plotted as the histogram in Fig. 4. We note this does not include the results from all the pairs within the data but also that the overall shape is similar to the plot of the OU(UK)'s CopyCatch results. From the set of 140 maximum values we are therefore able to calculate the correlation between the TeSLA results and those from Urkund, which also makes comparisons with the work submitted by the other students in the group. The correlations for all three tools are given in Table 4 below.

Fig. 4. The spread of results from the TeSLA tool at OU(NL). Where (X, Y] notation means that the percentage of plagiarism is greater than X and lower or equal to Y,

These values show that Urkund and TeSLA return comparable, though not identical, results. The differences may be explained by Urkund's checks against three different sources and TeSLA's check against one as described in Table 2. They did both identify the two documents uploaded twice as 100% matches.

Table 4. Correlations between results from the three plagiarism detection tools used by OU(NL) on the documents submitted by participants

	<i>TeSLA</i>	<i>SafeAssign</i>	<i>Urkund</i>
TeSLA	1		
SafeAssign	0.13	1	
Urkund	0.87	0.30	1

It is useful to plot all the largest values per student for all three tools on the same graph and shows the similarity between the TeSLA and Urkund values. All four 100% Urkund data points are coterminous with a TeSLA data point.

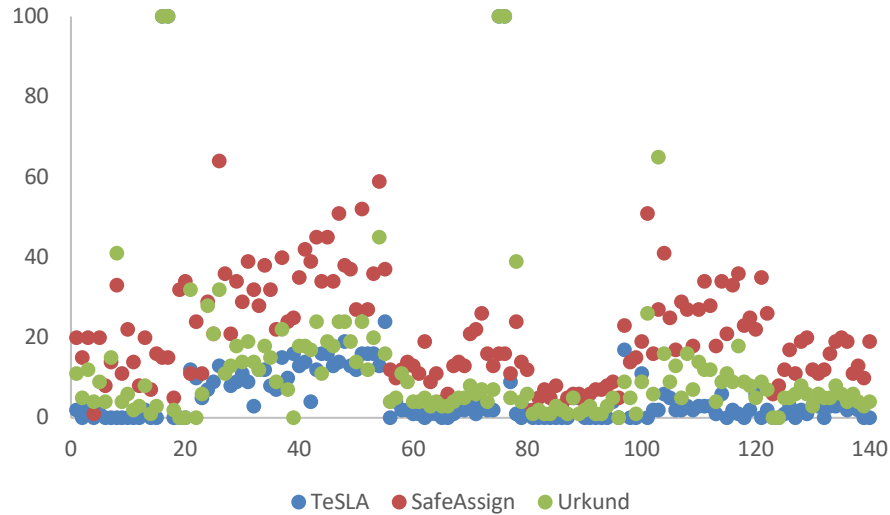


Fig. X. Percentage match for TeSLA, SafeAssign, Urkund at OU(NL) for each of the 140 documents

5 UOC results

The Open University of Catalunya fully embedded TeSLA within eight of their courses and involved 1,332 students in uploading at least one assessment to the TeSLA plagiarism detection tool. Depending on the course, students submitted up to six assessments, resulting in a total of 3,938 documents submitted. Unlike OU(NL) and OU(OUK), where students could only be invited once to participate, students at UOC may be involved more than once because they may study more than one of the included courses. All the results from their use of the TeSLA plagiarism detection tool are plotted in the histogram in Fig. 5. This stands out as looking different from that of OU(NL) and the CopyCatch plot from OU(UK) in that it rises considerably for matches over 80%. This is explained by the nature of the assessments in some of the courses, where students submit work that includes the question text: inevitably leading to considerable levels of matching. TeSLA does allow for this text to be ignored. However, this facility was not available at the time of the data collection. Once this is considered, the plot is broadly similar to that from OU(NL). Three of the courses include at UOC use Urkund. Logistical issues have prevented a direct comparison of the results from this with those of the TeSLA tool, although conversations with the tutors reveal anecdotally that there was broad agreement in the results from these

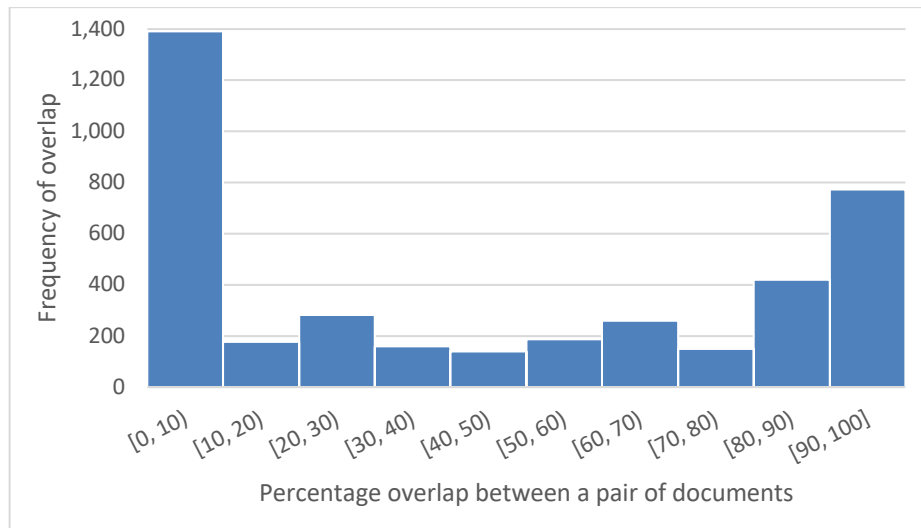


Fig. 5. The spread of results at UOC from the TeSLA tool. where [X, Y) notation means that the percentage of plagiarism is greater or equal to X and lower than Y.

6 Discussion

If we accept that a person is still required to make the final judgement in cases where plagiarism is suspected, any plagiarism detection tool must successfully identify documents with significant textual similarities to previously published work and to present the evidence to the academic tasked with making the judgement. This evidence should enable them to determine the level of severity of any plagiarism, perhaps using Turnitin's plagiarism spectrum, or an institutionally agreed guide. The output from each of the tools used within this study do provide this and provide the evidence of potential plagiarism needed by academics, as described by Woolls.

We found in bringing this data together that the TeSLA plagiarism tool does appear to offer results consistent across institutions, courses and with other tools that check evidence of collusion. Weber-Wolf et al note that the outputs from the various tools they tested are not in complete alignment [11], due to differences in system algorithm and this, together with the fact that Urkund checks both similarity with other students work and the originality of a submitted document is most likely to account for the differences between these two values as found in the OU(NL) case study.

The TeSLA plagiarism detection tool has an immediacy of response and an embeddedness within the VLE that we felt had considerable potential in helping students learn through immediate feedback. However, the rather obvious constraint that it can only give an accurate response as the last piece of work is submitted reduces the opportunity to assist students as they work, means that thought is needed if it is to be used in this way. Course design would perhaps need to include some unassessed activities where students each uploaded some writing and check their TeSLA 'score' once others had uploaded theirs. The tutor could then pick out examples to illustrate strong and poor

academic practice. In this way, both the embeddedness and immediacy of the tool are used to improve learning and constructive alignment between learning outcomes, learning and assessment could be supported.

We note that all the students who took part in this research gave their consent. Also, that it would be safe to assume that anyone who knew they had engaged in plagiarism, or was aware their academic practice was weak, would not take part. Or at least, would not submit any work they expected would be flagged by this specialist software. Having said this, it is our experience that most students that are flagged by plagiarism detection software are not aware they have engaged in plagiarism. From the results from OU(NL) we see that work we know is plagiarised is identified as a 100% match by TeSLA, as well as Urkund. Also, that the TeSLA results from UOC show levels of matching text all the way to the 90% to 100% bracket of values. The fact that these students are self-selecting and willing participants does not therefore appear to have prevented the tools from showing the full range of values. Technical problems did, on occasion impact the TeSLA results. However, this is understandable in the first trial at a large deployment of a new system.

When introducing new technologies into teaching and learning it is important to consider the layers of trust that exist within the university community. Even in trusted institutions we cannot take for granted that students, and staff, will trust such an innovation [18]. It is important therefore to be as transparent as possible about what these are, how they will be used and the benefits there will be from using them. An earlier analysis has shown that age is a factor in an individual's appreciation of cheating [19]. It was found that 'middle-aged participants were more aware of the nuances of cheating and plagiarism; while younger students were more likely to reject e-authentication'. These differences will need to be taken into account when introducing an embedded system like TeSLA.

7 Next steps

The TeSLA suite of tools and interface continue to be developed. The reflection, in this paper, on the three case studies shows the tool can provide a test for collusion between students. Together, we expect these to lead to further studies of the efficacy of the TeSLA tools and on how they can benefit, students, staff and institutions.

8 Conclusion

The TeSLA plagiarism detection tool does detect potential collusion between students and can give a full set of results immediately on submission of the last piece of work in any assessment. Although the TeSLA system is relatively immature when compared with the other systems in use, the plagiarism detection tool does provide a level of feedback that can support those responsible for dealing with plagiarism in students' assessments and does not meet the criteria of providing the evidence as set out by Woolls [3]. The TeSLA system is constructed in a way that enables it to be embedded within an institutional VLE and invoked seamlessly. In addition to providing the e-authentication

of students, this provides opportunities for improving the constructive alignment of learning outcomes describing the development of good academic practice and the avoidance of plagiaristic approaches and their learning and assessment: and thus the overall student experience. To do this successfully would need TeSLA considerations to be included within any learning design process in operation.

9 Acknowledgments

We gratefully acknowledge the support of Beryl Taylor and Stevie Eglinton-Pacitti of the Policy Exceptions and Academic Conduct team at the OU(UK) in providing the OU(UK) Turnitin and CopyCatch data used in this report. The CopyCatch data was also only possible with the assistance of the OU(UK) IT team, especially Adeola Adeliyi.

This project has been co-funded by the HORIZON 2020 Programme of the European Union; Project Number: 688520 – TESLA – H2020-ICT-2015/H2020-ICT-2015 Agreement Number: 688520. This publication reflects the views only of the author, and the Commission cannot be held responsible for any use, which may be made of the information contained therein.

References

1. ProQuest (2018) *About ERIC*. Available at: <https://proquest.libguides.com/eric> (Accessed: 24 August 2018).
2. Clarivate Analytics. (2018). Web of Science. Retrieved August 24, 2018, from <https://clarivate.com/products/web-of-science/>
3. Woolls, D. (2012). Detecting Plagiarism. In Lawrence M. Solan & Peter M. Tiersma (Eds.), *The Oxford Handbook of Language and Law* (pp. 1–16). Oxford University Press. <https://doi.org/10.1093/oxfordhb/9780199572120.013.0038>
4. Chowdhury, H. A., & Bhattacharyya, D. K. (2016). Plagiarism: Taxonomy, Tools and Detection Techniques. *19th National Convention on Knowledge, Library and Information Networking (NACLIN 2016)*. Retrieved from <http://arxiv.org/abs/1801.06323>
5. Turnitin. (2015). *The Plagiarism Spectrum: Tagging Ten Types of Unoriginal Work*. Retrieved from <https://www.turnitin.com/infographics/the-plagiarism-spectrum>
6. European Network for Academic Integrity (ENAI). (n.d.). Retrieved from <http://www.academicintegrity.eu/wp/>
7. Weber-Wulff, D., Möller, C., Touras, J., Zincke, E., Berlin, H., & Berlin, H. U. (2013). *Plagiarism Detection Software Test 2013*. Retrieved from <http://plagiat.htw-berlin.de/wp-content/uploads/Testbericht-2013-color.pdf>
8. Turnitin LLC. (2018). Turnitin. Retrieved September 2, 2018, from www.turnitin.com
9. CFL Software. (2018). CopyCatch Investigator. Retrieved September 2, 2018, from <https://www.cflsoftware.com/detection-1>
10. Blackboard. (2018). SafeAssign. Retrieved September 2, 2018, from <https://www.blackboard.com/safeassign/index.html>
11. Prio Infocenter AB. (2018). Urkund. Retrieved from <https://www.urkund.com/about-urkund/>

12. [1] The Open University, "Plagiarism Policy," Milton Keynes, 2017. Retrieved from <https://help.open.ac.uk/documents/policies/plagiarism>
13. Biggs, J. (1996). Enhancing teaching through constructive alignment. *Higher Education*, 32(3), 347–364. Retrieved from <http://www.jstor.org/stable/3448076>
14. Biggs, J. (2014). Constructive alignment in university teaching. *HERDSA Review of Higher Education*, 1. Retrieved from www.herdsa.org.au
15. Whitelock, D., Twiner, A., Richardson, J. T. E., Field, D., & Pulman, S. (2016). OpenEssay-ist: A supply and demand learning analytics tool for drafting academic essays. In *LAK '15 Proceedings of the Fifth International Conference on Learning Analytics And Knowledge* (pp. 208–212). Poughkeepsie, New York. <https://doi.org/10.1145/2723576.2723599>
16. Sharples, M., Adams, A., Ferguson, R., Gaved, M., McAndrew, P., Rienties, B., ... Whitelock, D. (2014). *Innovating Pedagogy policy makers*.
17. TeSLA Consortium. (2018). Trust-Based Authentication & Authorship e-Assessment Analysis (TeSLA). Retrieved August 30, 2018, from <http://tesla-project.eu/>
18. Edwards, Chris; Holmes, Wayne; Whitelock, Denise and Okada, Ale (2018). Student Trust in e-Authentication. In: *L@S '18: Proceedings of the Fifth Annual ACM Conference on Learning at Scale*, ACM, New York, article no. 42.
19. Okada, A., Whitelock, D., Holmes, W., & Edwards, C. (2018). e-Authentication for online assessment: A mixed-method study. *British Journal of Educational Technology*, BJET, In Press. <https://doi.org/10.1111/bjet.12608>