DOI https://doi.org/10.5281/zenodo.11002346

AN AUTOMATED STUDENT PLAGIARISM MANAGEMENT SYSTEM IN PRIVATE HIGHER EDUCATION – EFFICACY AND ADOPTION CONSIDERATIONS

Mohini Grobler

School of Management, Varsity College, Independent Institute of Education, Nelson Mandela Bay, South Africa

Abstract

The prevalence of student plagiarism poses a formidable challenge to academic integrity. This study presents incumbent factors and considerations in the implementation of an automated student plagiarism management system, grounded in the Technology Acceptance Model (TAM), at a private higher education institution. The TAM, recognized for its relevance in technology adoption, guides the design and implementation of the automated system, aiming to discern its impact on academic acceptance. Employing a mixed-methods approach, the research integrates quantitative analysis of usage statistics from the system and thematic analysis of open-ended surveys distributed to a purposive sample of academics.

The study spans 2021 to 2023, during which 2139 plagiarism cases were reported and managed by the automated system, revealing salient patterns. Notably, the codification of policy parameters within the TAM framework effectively redirects unintentional plagiarism cases towards rehabilitation programs, indicating nuanced handling of diverse infractions. Penalties for intentional plagiarism serve as deterrents, evidenced by reduced repeat offenses. This paper demonstrates the usefulness of TAM in transitioning from manual to automated systems and explores nuances of user support for technological advancements and administrative automation. Early acceptance levels, with lower subsequent usage, suggest a gradual decline in adoption of the technology.

The case study presented illuminates critical factors influencing the migration from manual to automated plagiarism systems, offering insights into the efficacy and adoption of such technology within an institution. Furthermore, the study aims to contribute to the consolidation of relevant Fourth Industrial Revolution (4-IR) semantics, weaving together themes of plagiarism, academic integrity, automated education systems, and the efficacy of technological adoption.

Keywords: Automation, TAM, Student Plagiarism Management, future technology, Administrative Processes

1 INTRODUCTION

Plagiarism poses severe ethical challenges for Institutions of Higher Education. The shift to remote learning practices has intensified the prevalence of student plagiarism. In more recent times, with the availability of online applications, such as Bard and Chat GPT, capable of natural language processing of Web-wide queries/searches using AI tools, an essay or software component can be composed for the user within a noticeably brief period. Referencing and citations are not necessarily based on empirically valid, peer-reviewed, or scientifically validated literature resources. The extent to which text is paraphrased, copied verbatim without quotation marks, or transcribed without acknowledgement using formal referencing standards, exacerbates the problems implicit in the detection of plagiarism.

Promoting academic integrity requires a system-wide strategy for understanding, defining, and addressing student plagiarism (Brown & Hammond 2022). There are numerous definitions of plagiarism, typically distinguished by whether it is intentional or unintentional. Recent studies have highlighted the main reasons leading to plagiarism, such as ease of access to information online (facilitating copy-and-paste without acknowledgement of sources), pressure due to academic deadlines, academic performance pressure, inadequate academic writing skills, haste-writing under pressure, lack of paraphrasing skills, a misconception of self-plagiarism, and students becoming habitual plagiarists (Zhang & Yi 2021; Partap et al. 2019; Jereb et al. 2018).

Unintentional plagiarism, or “cryptomnesia”, is often described as individuals producing work believed to be original, but in fact, has been previously produced by someone else or by themselves (Brown & Murphy 1989). Plagiarism includes various combinations of verbatim copying and improper paraphrasing, with inadequate source-acknowledgement/citation. Intentional plagiarism is widely regarded as including mosaic plagiarism, plagiarism of ideas, plagiarism of text, and self-plagiarism (recycling text from own previous submissions), all with deliberate lack of source-acknowledgement/citation. Unintentional plagiarism occurs mainly due to lack of awareness. According to an Australian study, only half of university students had read the academic policy on plagiarism, and confusion about what behaviour constitutes plagiarism, was evident (Gullifer & Tyson, 2014). Most students at Babcock University, Nigeria, lacked adequate understanding of plagiarism behaviours, often leading to unintentional plagiarism, in another study (Babalola, 2012). Shadiqi (2019) reported that students largely perceived their previously submitted works to be owned by themselves and that over half of the students believed that self-plagiarism should not constitute academic dishonesty. Ellery (2008) found that most faculty members did not provide information about self-plagiarism to their students. Halupa & Bolliger (2015) found that only about one-fourth of the students in their study reported recycling parts of their own previous assignments.

A study by Lee and Choe (2017) found that students who received clear guidance on plagiarism were less likely to plagiarise than those who did not receive clear guidelines. Understanding students’ perceptions regarding academic integrity and plagiarism can help institutions develop effective policies and interventions for prevention (Halupa & Bollige, 2015). Notwithstanding, other studies found a significant positive relationship between levels of awareness and incidence of plagiarism, indicating that awareness of what constitutes student plagiarism does not necessarily deter students from engaging in the behaviour (Pupovac, et al., 2010; Babalola, 2012; Khathayut & Walker-Gleaves, 2020). Goldstein (2004) asserted that the factors which influence policy compliance include intention to comply, perceived policy legitimacy, and self-efficacy. Self-efficacy describes an individual's belief in their ability to execute behaviors necessary to produce specific performance objectives (Bandura, 1977, 1986, 1997).

Awareness of the possible ramifications of plagiarism is a critical element in this milieu. A significant amount of research continues to be undertaken in response to high levels of student plagiarism in higher education institutions (de Maio et al., 2020; Mahmoud et al., 2020; Perkins et al., 2020; Sorea et al., 2021). New models have emerged over the last decade for strategies and systems for detection, penalties, and mitigation, based on deeper understanding of the underlying reasons behind student plagiarism (Glendinning, 2014). Beyond the protection typically afforded to tertiary students, the violation of plagiarism laws can lead to dire consequences, including author banning, damage to one’s professional reputation, termination of a position, and possible legal action (Luksanapruksa & Millhouse, 2016). Academics thus need to manifest respect for intellectual-property legal-rights, of attribution of academic credit, and of ethical compliance – an ethos of academic integrity - among themselves and their students.

While some institutions tend to view all occurrences of plagiarism as academic misconduct, others take a more nuanced approach. This is articulated through internal policy and procedures that aim to quantify 'levels' of severity (Ali, 2021). Measured approaches such as these tend to rely on guides and normative parameters to help assess the level of severity; typically including the experience of the student, the percentage of material plagiarised, and the likelihood of intention to deceive (Mahmud et al. 2021). Such judgements can lead to a wide range of prescribed outcomes, from educational guidance and support to expulsion from the institution (Torres-Díaz et al., 2018). However, the intent to deceive can be extremely difficult to establish. A study (Yorke et al., 2009) conducted on academic institutional policies and procedures, primarily in Australia, drawing comparisons with international institutions, attributed the inconsistencies in policy to variations in definition and the ability to determine intent in plagiarism. The findings suggest that the treatment of intent is particularly inconsistent. Further, the variations in plagiarism policies across different institutions and departments contribute to the difficulties in enforcing plagiarism policies (Bretag et al., 2019). These variations can lead to inconsistencies in identifying, investigating, and penalizing plagiarism, resulting in a lack of trust in the system and subsequently in the institution's research outputs (McCabe et al., 2008). Some academic institutions have strict policies that clearly define plagiarism and its consequences, while others have ambiguous policies that make it difficult to differentiate between unintentional and intentional plagiarism (Standler, 2000). The equivocality in come policies can also make it difficult for students to understand the expectations regarding academic integrity (Adam et al., 2017).

A paper by East (2009) describes holistic approaches to academic integrity and explains how constructive alignment could be used to promote a learning environment where student plagiarism is managed consistently. East (2009) concludes that plagiarism in higher education in developing countries is prevalent largely due to lack of awareness and comparatively weaker controlling mechanisms, threatening academic standards and hindering competitiveness among graduates. Faculty members who believe penalties are an effective approach to dealing with both intentional and unintentional plagiarism are more likely to address student plagiarism directly, while those who expect students to credit resources for all class work tend to adopt a more formal approach by reporting it to the administration (Singh & Bennington 2012). Whether to report student plagiarism or not is typically motivated by the faculty members' perceptions of how their administration would manage a report of plagiarism (Bennington & Singh, 2013).

It is therefore clear that student plagiarism management ideally requires an institutional ethos of academic integrity, emanating from a clear and accepted regulatory framework (jointly managed by academics and administration/management) - with clearly articulated/published definitions, processes, and penalties - and with accepted credibility among students and staff. Would an automated system for the management of plagiarism, which reduces subjectivity and equivocality, improve the manifestation of such an environment? This study explores critical success factors to be considered both in the development and the adoption of such an automated system.

The original manual process for managing plagiarism is illustrated below (Figure 1).

2 MANUAL STUDENT PLAGIARISM ADMINISTRATION PROCESS

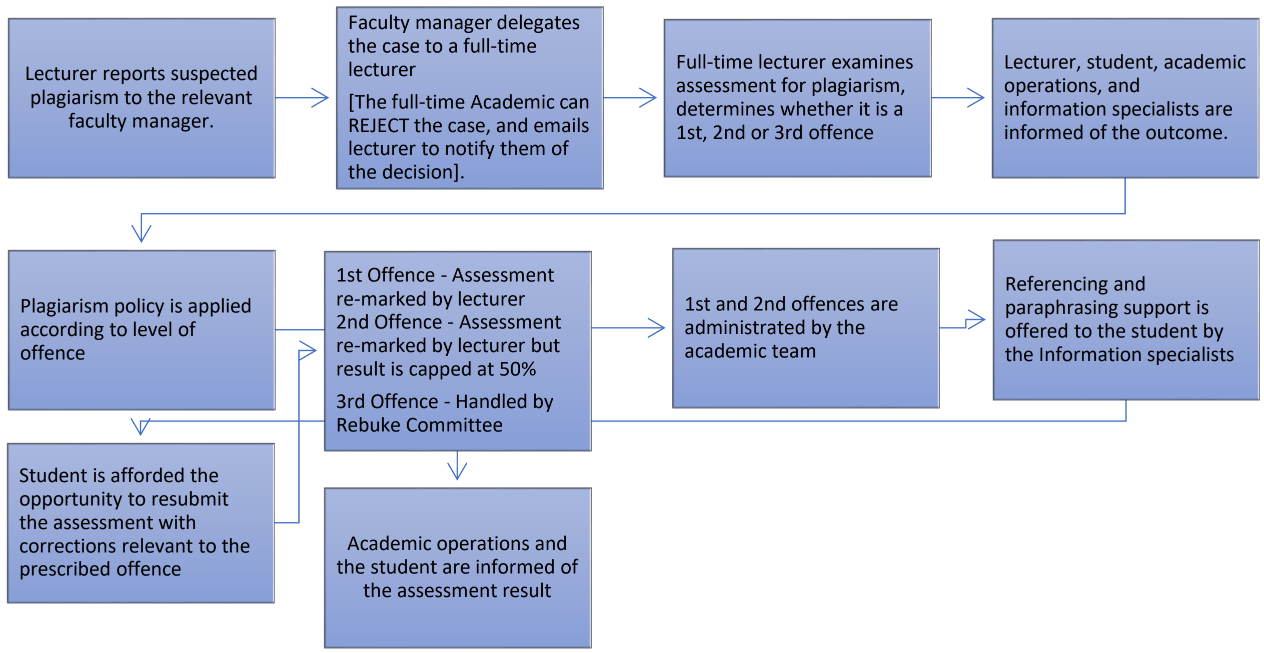

Figure 1: The manual plagiarism administration process

The manual process outlined in Figure 1 illustrates the administrative complexity involved in managing each case of suspected student plagiarism. If the lecturer suspects plagiarism, the case details, captured on a standard template, are emailed to the relevant faculty manager. The manager then delegates the case to an arbitrator (another full-time lecturer). The arbitrator then evaluates the parameters of the case and assigns a standardised severity status to the case:

- Rejected, rejected with a penalty for minor errors, or rejected with a penalty for major errors.

- Accepted, as 1st, 2nd, or 3rd offence (indicated on templated), for further action.

1st and 2nd offences are managed directly by the arbitrator. Students are given the opportunity to resubmit with amendments only to their referencing, within three days, and are offered referencing support by Information specialists. Resubmissions for 2nd offences are capped at a maximum mark of 50% if the resubmission has been deemed suitably amended. Students receive a letter, compiled from a template, on the details of the case. The information specialist provides support and ensures acknowledgement of the letter by the student. Amendments for 1st and 2nd offences are re-assessed with the intention of rehabilitating the student. 3rd offences are escalated to the relevant academic head for more severe disciplinary action.

3 PLAGIARISM PROCESS AUTOMATION

3.1 Automation – Critical Factors

The manual procedure is tedious and prone to subjective evaluation. In contrast, automation reduces/eradicates subjectivity, as policies are rule-based, can be codified into the system, and can be applied indiscriminately (Kamath et al. 2020). The administration of the rehabilitation process and the application of disciplinary measures for students can also be improved through automation (Patil et al. 2019). Automated plagiarism management software can also provide detailed reports that help academic management to identify the degree of prevalence of plagiarism per Faculty, as well as the efficiency of case management for the appropriate rehabilitation or disciplinary action (Bartlett, 2018). Implementing automation in plagiarism policy enforcement can also streamline the process of managing non-compliant submissions, leading to faster and more effective resolution. A study by Rodafinos (2018) examined the efficacy of a prescribed system's capacity to streamline the process, improve consistency, reduce errors and reduce the effort required by academic staff. It concluded that automated processes lead to more efficient human utilization, and a more streamlined plagiarism management process. Kamath et al. (2020) also found that by adopting technology, academic institutions can optimize their plagiarism management processes, leading to improved compliance and increased productivity. The efficiencies implicit in (automated) academic administration procedures provide a clear competitive advantage for various aspects of quality, motivates continuous improvements, and supports the achievement of educational objectives (Meza-Luque, et al., 2020). Further, a study conducted in Nigeria by Takwate (2018) revealed a significant relationship between academic administrative efficiency and students' academic performance.

Despite the obvious benefits of an automated system, the overall receptiveness of such systems by members within an institution remains a major detractor to adoption. According to Buchanan et al. (2013), faculty adoption of learning technologies is hindered by ease-of-use due to skills barriers and perceived usefulness. This highlights the need for end-user involvement in system development and for providing adequate technical support.

The Technology Acceptance Model was first introduced in 1986 by researchers Davis, Bagozzi and Warshaw as a means of predicting technology adoption. The model was developed to explain how individuals form attitudes towards modern technologies and how these attitudes influence their intention to use it, which is referred to as Behavioural Intention (BI). The TAM model proposed two key constructs, perceived usefulness (PU) and perceived ease-of-use (PEU), which were believed to determine an individual's BI. Perceived usefulness was defined as the "degree to which an individual believes that using a particular system would enhance his or her job performance" (Davis, 1993, p. 477). Perceived usefulness is predicated on expedience, time saving, effort saving, cost reducing, overall usefulness and job effectiveness (Yoshida 2016). PEU is defined in terms of being; easy to learn, controllable, clear, easy to understand, flexible, an easy path to proficiency, and easy to use (Davis, 1989). A study by Wang, Liang and Liang (2019) affirmed that perceived usefulness and ease-of-use were the most significant factors influencing the acceptance of e-learning systems, and that TAM was able to accurately predict the acceptance of these systems. In addition, a study by Javalgi, White and Ali (2022) found that TAM was more parsimonious and efficient in explaining the acceptance of technology by university educators when compared to the Unified Theory of Acceptance and Use of Technology (UTAUT) introduced by Venkatesh and Davis in 2000. In contrast, the results of another article (Turner 2010) show that while BI is likely correlated with actual usage, the TAM variables, perceived ease-of-use (PEU) and perceived usefulness (PU), are less likely correlated with actual usage.

A study by Davis (1989) constructed and validated novel scales for perceived usefulness (extent of functionality) and perceived ease-of-use (experienced useability), posited as fundamental determinants of user acceptance within the context of the Technology Acceptance Model (TAM). In two distinct studies involving 152 users and four application programs, two six-item scales emerged, exhibiting high reliabilities of .98 for perceived usefulness and .94, for perceived ease-of-use. Notably, in both studies, perceived usefulness demonstrated a markedly stronger correlation with usage behaviour compared to perceived ease-of-use. Regression analyses further indicated that perceived ease-of-use (usability) may function as a causal antecedent to perceived usefulness (functionality), rather than operating as a parallel and direct determinant of system usage. The findings offer significant implications for prospective research endeavours aimed at understanding user acceptance in technological contexts.

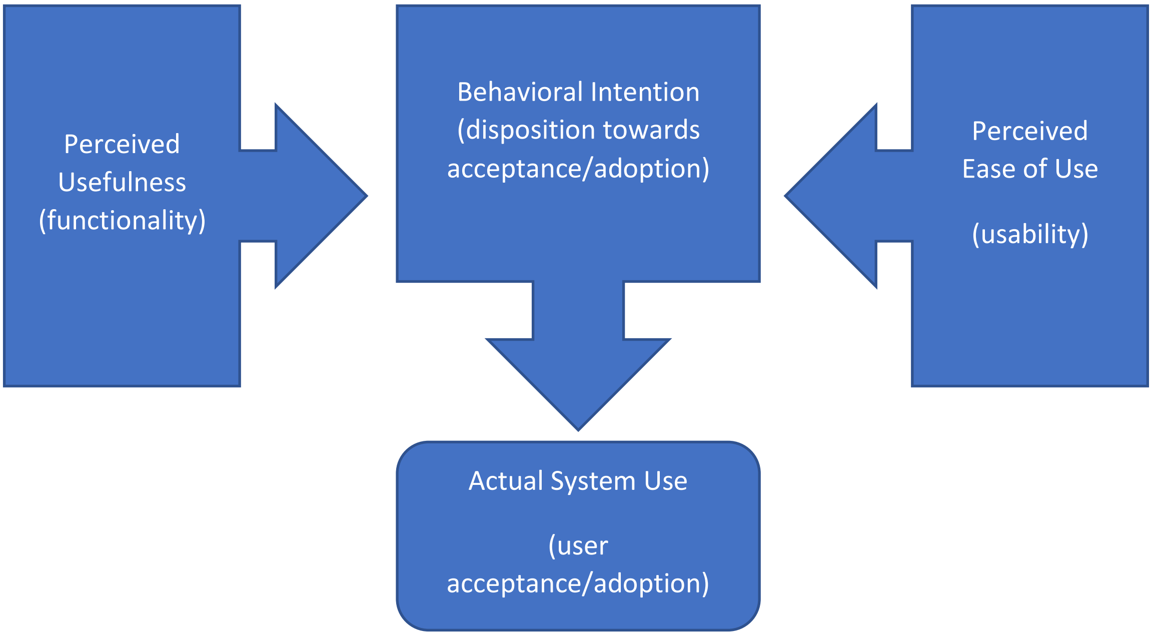

Figure 2: Adapted Technology Acceptance Model (TAM) Diagram. Adapted from Source: Davis (1989).

3.2 The Automated Plagiarism Management System – Technology and Workflow

This section describes an automated process for plagiarism management implemented by a private higher education institution. To ensure alignment with the rules and the objectives of the manual process, the incipient model mainly migrated repetitive, standard plagiarism-management workflow tasks to the automated system, such as facilitating specific identification of severity status and communication between relevant human and software agents. The initial assessment of whether an instance of plagiarism has arisen is still performed by academics (assessors and assessment moderators), using the institutional tools provided.

Challenges to the new systems were overcome through concerted efforts to make the system both useful and user-friendly for users. Microsoft © (2021), posits the Microsoft 365 applications, SharePoint, Teams, and Power Automate as powerful tools that can provide an elevated level of security and user-friendly facilitation (offering intuitive, familiar usability and functionality) to support academic processes. The built-in security features in SharePoint, such as user permissions and access controls, can be used to restrict access to sensitive information. Power Automate also offers data encryption and secure communication options to further protect sensitive data (Microsoft ©, 2021). Furthermore, SharePoint and Power Automate have user-friendly interfaces that make it easy for users to navigate the overall system and to access the specific functions and information they need (Microsoft ©, 2021). Forms can be customized to fit bespoke tasks in the academic process, such as collecting specific data from students or from faculty members (Microsoft ©, 2021).

Using SharePoint, Power Automate and Forms, specific focus was given to making the front-end interactions with the system useful (intuitive graphic user interface/GUI and navigability) and usable (responding as desired and expected, in simple and unambiguous manner). Lecturers initiate the plagiarism management process by completing a form - which is simplified in description and interpretation - by selecting inputs from pertinent drop-down lists exposed via checklist options, which best describes each case. The drop-down lists contain standard plagiarism offence parameters, from which users can compile the description which most accurately reflects the suspected plagiarism case. The basic parameters include 'No or incomplete reference list', 'paraphrasing issues', 'no in-text referencing', or 'no footnotes. More details are then requested in subsequent drop-down lists, which are prepopulated with more detailed options in cascading, decision-tree fashion.

Upon completion of the form, subsequent workflow tasks are instantiated. A plagiarism report is compiled, indicating the relevant parameters and the derived severity assessment. An initial email notification with links to the assessment evidence, is then generated and sent to a relevant, selected arbitrator, with the button options to either reject the case, or to re-assign the rehabilitation or rebuke measure generated in the previous step. 1st-, 2nd-, and 3rd-offence statuses are automatically detected from the related student unique identifier for the system-derived measure to address the specific offence. Should the arbitrator choose to not reject or attenuate the outcome, the student, the lecturer, the academic operations section, and the information specialists are all notified of the system-compiled decision via a system-generated email.

Students may then be offered individual academic support, based on the individual case. (All students are also required to complete a monitored online e-learning tutorial on plagiarism. Offenders are required to revisit the tutorial and to complete a subsequent assessment). Each case is captured via a SharePoint list with all student particulars being automatically retrieved from the form. All related documentation is housed in a SharePoint Library. The SharePoint (-Teams Dataverse) platform allows for restricted access, incorporates view controls, and provides a centralized (MS-SQL Server) database. Each stage of the process is tracked on the list as an integrated task in the Power Automate flows (workflows). The Power Automate flows are used to send reminders, notifications and e-mails to all parties within pre-specified timeframes, incorporating SharePoint and Teams facilitation.

4 RESULTS AND DISCUSSION – QUANTITATIVE ASSESSMENTS OF PERCEIVED-EFFICACY AND OF ADOPTION

In October 2021, the student plagiarism management process was automated and implemented across 5 faculties in a Private Higher Education Institution. This process was designed primarily to facilitate the rehabilitation of students found guilty largely due to negligence or ignorance. There are 14 primary selection options, which cascade to 301 possible (decision-tree) automated variations in the plagiarism case descriptions. The plagiarism system has, since inception, been used to report 2139 suspected cases as of December 2023. The table below (Table1) represents an Excel Power Pivot report, depicting information processed from a Power Pivot Data Model. It summarises aggregated data on plagiarism cases from October 2021 to December 2023 at the institution in the case study.

% Distribution of Case Results 2021 - 2023	**Year**			
	2021	**2022**	**2023**	**Average**
1st Offence	35%	36%	37%	36%
2nd Offence	16%	24%	18%	20%
3rd Offence	2%	3%	2%	2%
Same Assessment cycle - second 1st Offence	0%	6%	6%	4%
Same Assessment cycle - second 2nd Offence	0%	4%	4%	3%
Incomplete Cases	37%	13%	13%	20%
No penalty, student cleared	10%	5%	8%	7%
-5% Deduction from overall percentage - at least 5 MINOR errors in consistency, technical correctness, congruency, and reference list.	0%	1%	5%	2%
10% Deduction from overall percentage- at least 5 MAJOR errors in consistency, technical correctness, congruency, and reference list and mandatory Referencing workshop attendance	0%	8%	7%	5%
Grand Total	**100%**	**100%**	**100%**	**100%**

Table 1: Student Plagiarism Case Results Percentages by year: 2021 - 2023

The contents of Table 1 will be elaborated next to illustrate efficacy in automation. The average for 1st Offences over the 3 years was 36% of the total, for 2nd offences it was 20%, and only 2% were 3rd Offences. The 16% drop in 1st to 2nd offences could be attributed to the effectiveness of the rehabilitation, and targeted awareness created by the 1st offence. These added efficiencies (the real-time information and intelligence) are facilitated by the of the automated reporting and management systems. The Pivot Table and related visualisations (various graphs, gauges, and others) provide real-time viewing of selected key performance indicators.

Qualitative conclusions can also be drawn from the available data. As an example, the relative consistency of percentages for each category of offence over the three-year period indicates that measures to reduce plagiarism appears to not have produced the desired effect.

The table also illustrates the diversity of possible bespoke metrics that have peculiar institutional significance that could be captured (via system GUIs) and analysed. Unless data for each manual case is meticulously captured, such analyses are not readily available in a manual system.

For instance, in 2021, 37% of cases were left unresolved. The 'Incomplete' process cycles represent a sizeable proportion of cases reported by Lecturers. It can be deduced that arbitrators appear to not have adopted the system as readily as had been desired.

Although only fundamental information is presented, detailed business intelligence can be gleaned from the Power Pivot reports, depending on the detail captured in the related tables of the Data Model. (The Power Pivot Data Model is based on Data Warehouse concepts – inter alia, Fact Tables, Dimension Tables, Measures, calculated columns based on complex Data Analysis Expressions/DAX, Key Performance Indicators/KPIs, perspectives, and security groups). Power Pivot facilitates drill-down to expose specific cascaded data. This also enables the application of AI algorithms for comprehensive analytics (decision-making predictions based on AI-inferred patterns and trends). As an example, specific student profiles (based on academic parameters or otherwise) can be inferred for categories of plagiarism offences (from historical data, using machine-learning tools). New students fitting the inferred profiles can then be flagged as at-risk and pre-emptive measures could be implemented. (In many jurisdictions, personal privacy laws require consent to be obtained from the data-subject). A major detractor in the application of Data Science concepts to enhance the automated system is the ubiquitous lack of common proficiency, thus potentially lowering ease-of-use and usefulness (and thus, usage) of the system. Usage and adoption of the system in the case study is described based on quantitative metrics in subsequent paragraphs.

In the next illustration (Table 2), the percentage of total number of cases reported by each of five Schools over the same three-year period is indicated.

	Percentage of Total Cases by Year			
School	**2021**	**2022**	**2023**	**Average**
SoE (Education)	29%	28%	24%	27%
SoHSS (Human & Social Sciences)	6%	9%	15%	9%
SoIT (Information Technology)	13%	12%	22%	15%
SoL (Law)	13%	20%	17%	17%
SoM (Management)	40%	30%	23%	31%
Grand Total	**100%**	**100%**	**100%**	

Table 2: Percentage of Total Cases Reported on the Automation System by School (2021 – 2023)

Table 2 provides a comparison within each School over the period. The data seems to suggest that SoM and SoE had the highest usage of the system in 2021 – 2022, with significant drops in reported cases by 2023. This pattern is similarly high for SoL in 2022, with a subsequent drop in 2023. The drop in reported cases could be attributed to increased awareness of plagiarism in the respective Schools. SoIT and SoHSS, however, appear to have both experienced a steady increase over the 3 years.

There are obvious variables, such as specific School enrolment numbers, contributing to the numbers of reported cases per School each year. Comparisons of reported cases across Schools would therefore be immaterial. By presenting usage per School, over the three-year period, as a percentage of the total institutional reported cases for each year, School-specific factors are negated to some extent. Presuming that the directive that every case be reported on the system is diligently observed, usage within each School (over the three-year period) is accepted as being congruent with the pattern of reported cases.

In Table 3, the reported cases for 2022 and 2023 are indexed against those for 2021, per School, as an indication of changes in usage trends over the succeeding 2 years. This obviates factors beyond each School that would impact reported cases/usage.

Indexed Case Count per School	Year 2021	2022	2023
SoE	1.06	1.04	0.88
SoHSS	0.59	0.92	1.58
SoIT	0.86	0.81	1.43
SoL	0.75	1.21	1.00
SoM	1.28	0.97	0.72

Table 3: Indexed Number of Reported Cases by School (2021 – 2023)

To examine and compare adoption within each School, over the circumscribed period, 3 categories to describe the levels of system acceptance, based on usage, were used (Table 3): High Acceptance (>1) Medium Acceptance (>0.75, <1) and Low Acceptance (<0.75). Usage, in turn, was loosely predicated on the number of individual cases processed through the automated student plagiarism management system, as mentioned earlier. SoM (1.28) and SoE (1.06) showed high acceptance in the year of implementation (2021), with progressively lower levels of usage subsequently. By comparison, SoIT (0.86) and SoL (0.75) presented medium rates of acceptance with a considerable increase over the succeeding 2 years. SoHSS (0.59) however, posted the lowest level of acceptance in 2021 but the highest acceptance (1.58) across all Schools 2 years later.

Count of Student Name	Year			
Case Result	2021	2022	2023	Grand Total
Incomplete	**58%**	**24%**	**18%**	**100%**
SoE	8%	6%	8%	21%
SoHSS	4%	5%	5%	14%
SoIT	7%	0%	0%	8%
SoL	6%	10%	2%	18%
SoM	32%	4%	3%	39%
Grand Total	**58%**	**24%**	**18%**	**100%**

Table 4: Percentage of Incomplete Cases on the Automated System by School per Year

The percentage of incomplete cases in Table 4 provided an additional metric of acceptance by faculty (arbitrators). As highlighted by Table 1, 37% of total cases were incomplete and not resolved by the arbitrators. The Faculty of Management is a clear outlier in 2021, but with a marked improvement in 2022 and 2023, which represents a considerable drop in incomplete cases. The Faculty of IT exhibited medium levels of acceptance in 2021 but posted the lowest number of incomplete cases in 2022 and 2023.

To test these initial conclusions and to understand the dynamics between ease-of-use and perceived usefulness that impact behavioural intention towards the automated system, a survey was conducted. In 2022, representatives from the full-time academic team were selected to complete an open-ended survey on both the manual system and the automated system. The members were selected to incorporate representatives from Schools with higher usage cases, highest number of incomplete cases, lowest usage levels and least technological barrier. (The data collected was anonymized to maintain confidentiality). While institution-specific themes emerged in the data, definitive correlations to the TAM factors PU and PEU were observed. Simplified aggregations of the data are depicted in the figures below.

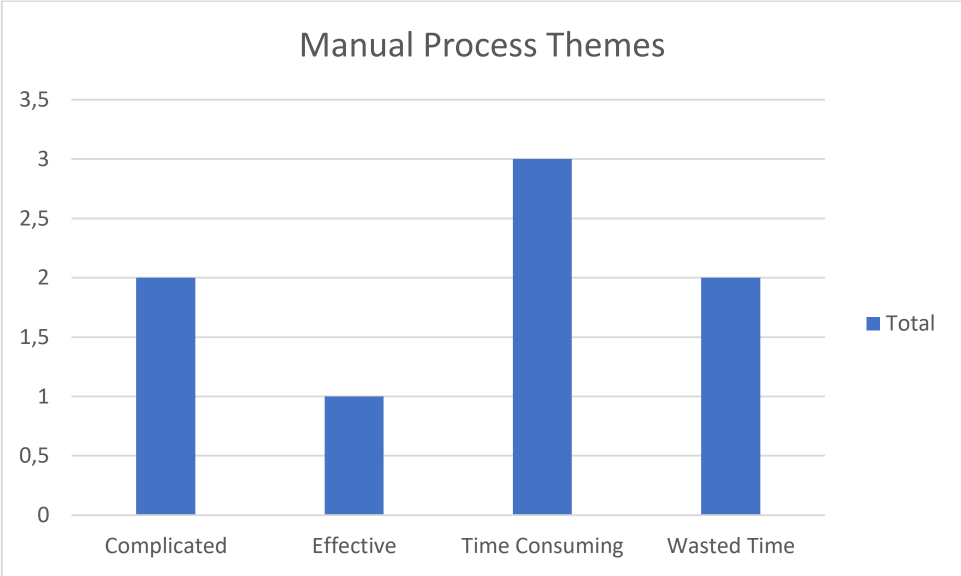

Figure 3: Themed Perception Ratings of the Manual System

The manual process was generally perceived as time-consuming, complicated, with time being wasted on administrative tasks. Only one respondent considered the manual system effective (except for the time spent on email communication).

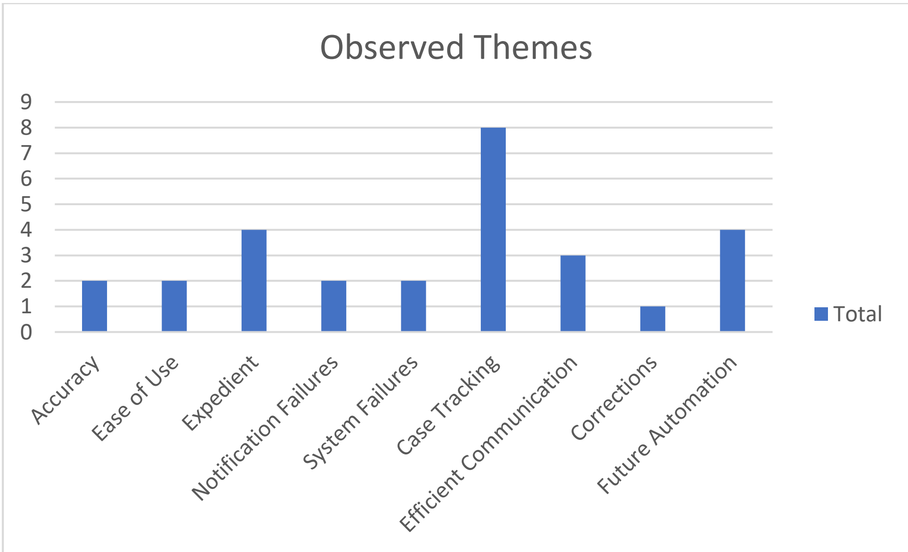

Figure 4: Themed Perception Ratings of the Automated System

For the automated process, the most frequently occurring theme was "Case Tracking". Within Case Tracking, sub-themes such as "Expedient" and "Accuracy" emerged as crucial considerations. Ease-of-use was another prominent theme, indicating the importance of user-friendly experiences. The data also revealed concerns about system failures and notification failures, highlighting potential challenges that users may have encountered. Interestingly, some respondents expressed complete satisfaction by reporting "No Issues." Moreover, a notable theme was the endorsement of future automation support, suggesting a positive outlook towards technological advancements and automation within the surveyed context. Overall, the data provides decision-supporting insights into user perceptions of the significance of efficient case tracking, ease-of-use, and anticipation for future automation support.

Schools	Themes	Frequency Rating	Usage 2021	Usage 2022	Usage 2023
SoE	Ease-of-use	2	29%	28%	24%
SoE	Perceived Usefulness	4			
SoHSS	Ease-of-use	3	6%	9%	15%
SoHSS	Perceived Usefulness	4			
SoIT	Ease-of-use	0	13%	12%	22%
SoIT	Perceived Usefulness	5			
SoM	Ease-of-use	1	40%	30%	23%
SoM	Perceived Usefulness	5			

Table 5: TAM Theme Frequency Rating versus Corresponding Faculty Usage Pattern (2021 – 2023)

The data in Table 5 presents information on the frequency rating of themes associated with different Schools and their corresponding usage patterns over three years.

For the "Ease-of-Use" theme versus usage:

The School of Education (SoE) has a lower ease-of-use frequency rating (2), consistent with decreasing usage from 2021 to 2023. The Faculty of Humanities and Social Sciences (SoHSS), on the other hand, has a higher ease-of-use frequency rating (3), with usage increasing in 2021 to 2023. The Faculty of Information Technology (SoIT) has an ease-of-use frequency rating of 0, but its usage increased considerably from 2021 to 2023. However, consideration must be given to the lack of technical barrier for the Faculty of Information Technology (SoIT), illuminating 'ease-of-use' as a non-entity consideration when user interfaces are based in familiar operating systems.

For the "Perceived Usefulness" theme versus usage:

The School of Management (SoM) and SoE each have a usefulness frequency rating of 5, but each shows a decrease in usage from 2021 to 2023. Aligning to earlier findings of early adoption resulting in a decrease in reported cases in the succeeding years. The Faculty of Information Technology (SoIT) indicated the highest levels of perceived usefulness, upon further investigation it was determined the increase in reported cases was related to the growth of the Faculty and addition of a qualification. The 2023 increase in usage to 22% aligned to the theoretical and business based modules introduced during the year. The Faculty of Humanities and Social Sciences (SoHSS) indicated moderately high perceived usefulness however, commented on the efficiency of the manual system. Illuminating the possible reasons for adoption delays.

To assess the impact of Perceived Ease-of-Use and Perceived Usefulness on user acceptance over the three consecutive years (2021, 2022, and 2023), regression analyses were conducted. The analyses illustrate the varying degrees of correlation of these key variables across the observed years. (The Multiple R values indicate the strength of the relationship, while R Square and Adjusted R Square offer insights into the proportion of variance and the model's robustness, respectively. Standard Error values provide an assessment of the average deviation between observed and predicted values). This examination emphasises the dynamic nature of user acceptance as influenced by perceived ease-of-use and perceived usefulness, offering a nuanced understanding of their evolving roles over time (Stoffel et al. 2021; Strub, M., & Cieszewski, C. 2012).

Regression Statistics	2021	2022	2023	Interpretation
Multiple R	0.98	0.90	0.78	Strong positive correlation
R Square	0.96	0.82	0.61	High proportion of variance explained
Adjusted R Square	0.92	0.64	0.22	Robust model, adjusting for predictors
Standard Error	0.29	0.60	0.88	Low average deviation between observed and predicted
Observations	3	3	3	Number of data points included in the analysis

Table 6: Regression Statistics for Perceived Ease-of-use and Actual Usage 2021 - 2023

The Multiple R values indicate a strong positive correlation between Perceived Ease-of-use and the dependent variable in each respective year. The R Square values demonstrate that a high proportion of the variability in the dependent variable is explained by Perceived Ease-of-use, with the explanation becoming less robust in later years. Adjusted R Square, adjusting for predictors, suggests the model's robustness, with a notable decrease in explanatory power in 2023. The Standard Error values show a low average deviation between the observed and predicted values, with an increase in deviation in 2023.

Regression Statistics	2021	2022	2023	Interpretation
Multiple R	0.35	0.15	0.40	Weak to moderate positive correlation
R Square	0.12	0.02	0.16	Low proportion of variance explained
Adjusted R Square	-0.32	-0.46	-0.26	Poor model fit, negative values indicate a worse fit
Standard Error	0.66	0.70	0.65	Moderate average deviation between observed and predicted
Observations	4	4	4	Number of data points included in the analysis

Table 7: Regression Statistics for Perceived Usefulness and Actual Usage 2021 - 2023

The Multiple R values indicate a weak to moderate positive correlation between Perceived Usefulness and the usage in each respective year. The R Square values demonstrate a low proportion of the variability in usage explained by Perceived Usefulness. Adjusted R Square values are negative, indicating a poor fit of the model, and negative values suggest that the model fit might be worse than a simple mean. The Standard Error values show a moderate average deviation between the observed and predicted values.

Regression Statistics	**2021**	**2022**	**2023**
Multiple R	0.65 (Moderate correlation)	0.60 (Moderate correlation)	0.20 (Weak correlation)
R Square	0.42 (42% variability)	0.36 (36% variability)	0.04 (4% variability)
Adjusted R Square	0.27 (Possible overfitting)	0.20 (Possible overfitting)	-0.20 (Model may not fit)
Standard Error	1.25 (Avg. distance: 2021)	1.32 (Avg. distance: 2022)	1.61 (Avg. distance: 2023)
Observations	6	6	6

Table 8: Regression Statistics for TAM Independent Variables and Actual Usage 2021 - 2023

In a study by Davis (1989), demonstrating robust convergent, discriminant, and factorial validity, perceived usefulness displayed a significant correlation with both self-reported current usage (r=.63, Study 1) and self-predicted future usage (r=.85, Study 2). Similarly, perceived ease-of-use exhibited significant correlations with current usage (r=.45, Study 1) and future usage (r=.59, Study 2).

The regression analysis for the years 2021, 2022, and 2023 in Table 7 reveals some insights into the relationship between TAM (Technology Acceptance Model) factors - specifically, ease-of-use and perceived usefulness - and the corresponding usage. The multiple correlation coefficient (Multiple R) demonstrates a consistently moderate positive correlation in 2021 (0.65) and 2022 (0.60), indicating a meaningful connection between the independent variables and usage. However, in 2023, the Multiple R drops to 0.20, suggesting a weakening correlation. The R Square values further elucidate the model's explanatory power, with 42% and 36% of the variability in usage accounted for in 2021 and 2022, respectively, but a sharp decline to only 4% in 2023. Notably, the Adjusted R Square values of 0.27 and 0.20 raise concerns about potential overfitting in 2021 and 2022, while the negative value (-0.20) in 2023 suggests that the model may not be an adequate fit for the data. Additionally, the Standard Error values provide insights into the average distance between observed and predicted values, highlighting potential variations in predictions across the years. Overall, the findings indicate the need for a closer examination of the model's reliability and the factors influencing usage dynamics over time. It is highly conceivable that increased awareness and rehabilitation facilitated by the system has effectively reduced the number of suspected student plagiarism cases reported, thereby confounding usage patterns.

The observed patterns, as delineated by Multiple R, R Square, Adjusted R Square, and Standard Error values, emphasise the nuanced interplay between these crucial variables and their impact on measured user behaviour. Notably, the varying strengths of correlation and explanatory power over the studied period indicate a dynamic relationship between users and technology, offering valuable insights into the nuanced evolution of perceptions regarding ease-of-use and perceived usefulness. These findings contribute to a more profound comprehension of the factors influencing user acceptance, providing a foundation for future research endeavours and strategic considerations in technology adoption. It is worth noting that despite higher adoption disposition, usage might be lowered by successful outcomes, in instances where the system is intended to lower workloads.

In Table 9, to assess the level of intentional and unintentional plagiarism in the reported cases, the list of descriptions was categorised according to the definitions outlined by the literature (Brown & Murphy, 1989; Gullifer & Tyson, 2014; Babalola, 2012; Shadiqi, 2019; Pupovac, et al., 2010; Babalola, 2012; Khathayut & Walker-Gleaves, 2020).

Intentional or Unintentional Plagiarism	**Year**			
Penalty Applied (Yes/ No)	**2021**	**2022**	**2023**	**Grand Total**
Intentional	**31%**	**32%**	**25%**	**89%**
No	17%	21%	15%	54%
Yes	15%	11%	10%	36%
Unintentional	**1%**	**8%**	**3%**	**11%**
No	0%	3%	0%	4%
Yes	1%	4%	3%	7%
Grand Total	**32%**	**40%**	**28%**	**100%**

Table 9: Total Reported Intentional and Unintentional Plagiarism cases

The data in Table 9 merely outlines the occurrences of intentional and unintentional plagiarism instances over the course of three years (2021, 2022, and 2023), categorized by virtue of the penalties applied. Notably, the figures indicate a consistent prevalence of intentional plagiarism, with 31%, 32%, and 25% of cases recorded for the respective years. Conversely, the incidence of unintentional plagiarism with no penalty meted out, follows a fluctuating pattern, registering only 4 cases in 2021, peaking at 3% of cases in 2022, and subsequently decreasing to 0 cases in 2023; perhaps indicating no unintended, unjustifiably reported cases. The cases of unintentional plagiarism with imposition of penalties also exhibits variability, with 1% cases in 2021, increasing to 4% in 2022, and further diminishing to 3% in 2023. Additionally, instances of negligence leading to plagiarism are noteworthy, with 1% of cases in 2021, surging to 8% in 2022, and decreasing to 3% in 2023. The breakdown of plagiarism incidents and associated penalties provides some insights into context-related variables and potential areas requiring interventions or educational strategies. While such information is easily aggregated from raw data in an automated system, it can be transformed into useful metrics for localised heuristics.

Student Count	Year			
Case Result	**2021**	**2022**	**2023**	**Grand Total**
Intentional	**31%**	**32%**	**25%**	**89%**
10% Deduction from overall percentage - - at least 5 MAJOR errors in consistency, technical correctness, congruency, and reference list and mandatory Referencing workshop attendance	0%	1%	1%	3%
1st Offence	11%	12%	10%	33%
2nd Offence	5%	8%	5%	18%
3rd Offence	1%	1%	1%	2%
-5% Deduction from overall percentage - at least 5 MINOR errors in consistency, technical correctness, congruency, and reference list.	0%	0%	1%	1%
Incomplete	11%	4%	3%	19%
No penalty student cleared	3%	2%	2%	7%
Same Assessment cycle - second 1st Offence	0%	2%	2%	4%
Same Assessment cycle - second 2nd Offence	0%	2%	1%	3%
Unintentional	**1%**	**8%**	**3%**	**11%**
10% Deduction from overall percentage - - at least 5 MAJOR errors in consistency, technical correctness, congruency, and reference list and mandatory Referencing workshop attendance	0%	2%	1%	3%
1st Offence	0%	2%	0%	3%
2nd Offence	0%	1%	0%	1%
3rd Offence	0%	0%	0%	0%
-5% Deduction from overall percentage - at least 5 MINOR errors in consistency, technical correctness, congruency, and reference list.	0%	0%	1%	1%
Incomplete	0%	1%	0%	2%
No penalty student cleared	0%	0%	0%	1%
Same Assessment cycle - second 1st Offence	0%	0%	0%	0%
Grand Total	32%	40%	28%	100%

Table 10: Penalties Applied to Intentional and Unintentional Reported Cases

Table 10 incorporates specific institutional penalties and supplementary concepts related to plagiarism management. The Table indicates that 7% of total cases are rejected by arbitrators. The “Same Assessment cycle” options were introduced in late November 2021 to allow students who were guilty of the same offence to not be penalized until remedial action has occurred; reinforcing that the focus is on rehabilitation. 36% of negligent cases incur a 5 or 10% deduction penalty from the arbitrators, while only 4% of intentional cases are assigned this lesser penalty. 36% of negligent cases were classified as 1st or 2nd offences. While both offences are eligible for resubmission - with only reference amendments - 2nd offences are capped at 50% of the maximum marks. However, 58% of cases with descriptions aligned to intentional plagiarism incurred 1st or 2nd offence classifications. Cascading penalties are designed to rehabilitate students and to serve as a warning to students who are at risk of violating the policy. After an initial 24% increase from 2021 to 2022 in total cases reported to the system, 2022 to 2023 showed a 30% decrease in cases. 89% of cases were intentional, specifically omitting in-text referencing or failing to include a reference list.

5 CONCLUSION

This research navigates the intricate landscape of student plagiarism management. It advocates for the adoption of an Automated Student Plagiarism Management System, with the design and implementation being underpinned by the Technology Acceptance Model (TAM). The emergence of meaningful patterns from the analysis of 2139 cases over the span of 2021 to 2023, emphasises the transformative potential of this technology. TAM-based system design can manifest nuanced policy enforcement. It can, for instance, direct unintentional infractions towards rehabilitation, while effectively deterring intentional plagiarism through judicious penalties.

The observed correlation between early acceptance levels and subsequent usage patterns suggests a gradual normalization of the technology-based paradigm. This study, employing a mixed-methods approach to assessing efficacy and adoption, also affirms the efficacy of TAM in facilitating the seamless transition from manual to automated management systems. Furthermore, the overwhelming support voiced by academics for future technological advancements and administrative automation echoes a promising receptivity to the evolving landscape of educational technology.

As a case study in the broader discourse of the Fourth Industrial Revolution, this research illuminates critical factors influencing the migration to automated systems and offers a lens through which to understand the efficacy and adoption of transformative technologies within higher education institutions. These findings unequivocally support the pragmatic incorporation of automated systems to fortify the foundations of academia.

REFERENCE LIST

Adam, L., Anderson, V., & Spronken-Smith, R. (2017). ‘It’s not fair’: policy discourses and students’ understandings of plagiarism in a New Zealand university. Higher Education, 74, 17-32. https://doi.org/10.1007/S10734-016-0025-9.Bandura, A. (1977). Self-efficacy: Toward a unifying theory of behavioural change. Psychological Review, 84(2), 191-215.

Ali, M. (2021). Attitudes towards plagiarism among faculty members in Egypt: a cross-sectional study. Scientometrics, 126, 3535-3547. https://doi.org/10.1007/s11192-021-03872-8.Bandura, A. (1986). Social foundations of thought and action: A social cognitive theory. Englewood Cliffs, NJ: Prentice-Hall.

Bandura, A. (1997). Self-Efficacy: The exercise of control. New York, NY: W. H. Freeman. Bennington, A., & Singh, H. (2013). Faculty Expectations of Administration: Predictors of Intention to Report Student Plagiarism. The Academy of Educational Leadership Journal, 17, 63.

Brown, A., & Murphy, D. (1989). Cryptomnesia: Delineating inadvertent plagiarism. Journal of Experimental Psychology: Learning, Memory and Cognition, 15, 432-442. https://doi.org/10.1037/0278-7393.15.3.432.

Brown, S., & Hammond, K. (2022). Plagiarism in Higher Education: Navigating a Perfect Storm. *European Journal of Education and Pedagogy*. https://doi.org/10.24018/ejedu.2022.3.5.452.

Buchanan, T., Sainter, P., & Saunders, G. (2013). Factors affecting faculty use of learning technologies: implications for models of technology adoption. Journal of Computing in Higher Education, 25, 1-11. https://doi.org/10.1007/s12528-013-9066-6.

Doghonadze, N., Pipia, E., & Parjanadze, N. (2018). Institutional Plagiarism Policy (Georgian higher education institutions' case). Journal of Education in Black Sea Region. https://doi.org/10.31578/JEBS.2018.3.2.10.

East, J. (2009). Aligning policy and practice: An approach to integrating academic integrity. *Journal of Academic Language and Learning*, 3.

Ellery, K. (2008). Undergraduate plagiarism: a pedagogical perspective. Assessment & Evaluation in Higher Education, 33, 507 - 516. https://doi.org/10.1080/02602930701698918.

Gullifer, J., & Tyson, G. (2014). Who has read the policy on plagiarism? Unpacking students' understanding of plagiarism. Studies in Higher Education, 39, 1202 - 1218. https://doi.org/10.1080/03075079.2013.777412.

Halupa, C., & Bolliger, D. (2015). Student Perceptions of Self-Plagiarism: A Multi-University Exploratory Study. Journal of Academic Ethics, 13, 91-105. https://doi.org/10.1007/S10805-015-9228-4.

Jereb, E., Perc, M., Lämmlein, B., Jerebic, J., Urh, M., Podbregar, I., & Sprajc, P. (2018). Factors influencing plagiarism in higher education: A comparison of German and Slovene students. PLoS ONE, 13. https://doi.org/10.1371/journal.pone.0202252.

Khathayut, P., & Walker-Gleaves, C. (2020). Academic faculty conceptualisation and understanding of plagiarism – a Thai university exploratory study. Journal of Further and Higher Education, 45, 558 - 572. https://doi.org/10.1080/0309877X.2020.1795093.

Luksanapruksa, P., & Millhouse, P. (2016). Guidelines on What Constitutes Plagiarism and Electronic Tools to Detect it. *Clinical Spine Surgery*, 29, 119–120. https://doi.org/10.1097/BSD.0000000000000371.

Moore, D. (1995). Academic integrity. *BMJ*, 311 7004, 573. https://doi.org/10.4018/978-1-60960-543-8.ch007.

Partap, B., Kumar, R., & Singh, B. (2019). Plagiarism and Fair Use of Copyrighted Work: Awareness Survey among Doctoral Students of CCS Haryana Agricultural University, Hisar, India. Library Progress (International). https://doi.org/10.5958/2320-317X.2019.00009.6.

Patil, A., Jadhav, N., Sargar, S., & Jayachandran, S. (2019). Faculty Automation System. Journal of emerging technologies and innovative research.

Pupovac, V., Bilic-Zulle, L., Mavrinac, M., & Petrovecki, M. (2010). Attitudes toward plagiarism among pharmacy and medical biochemistry students - cross-sectional survey study. Biochemia Medica, 20, 307-313. https://doi.org/10.11613/BM.2010.039.

Singh, H., & Bennington, A. (2012). Faculty on the Frontline: Predicting Faculty Intentions to Address College Student Plagiarism. The Academy of Educational Leadership Journal, 16, 115.

Saeed, S., Aamir, R., & Ramzan, M. (2011). Plagiarism and its implications on higher education in developing countries. International Journal of Teaching and Case Studies, 3, 123. https://doi.org/10.1504/IJTCS.2011.039552.

Shadiqi, M. (2019). Memahami dan Mencegah Perilaku Plagiarisme dalam Menulis Karya Ilmiah. Bulletin Psikologi. https://doi.org/10.22146/BULETINPSIKOLOGI.43058.

Stoffel, M., Nakagawa, S., & Schielzeth, H., 2021. partR2: partitioning R2 in generalized linear mixed models. PeerJ, 9. https://doi.org/10.7717/peerj.11414.

Strub, M., & Cieszewski, C. (2012). Generalization of the Coefficient of Determination or R-square and its application to Self-Referencing Models. Math. Comput. For. Nat. Resour. Sci., 4, 73-76.

Yorke, J., Lawson, K., & McMahon, G. (2009). Can we reliably determine intent in cases of plagiarism? The International Journal for Educational Integrity, 5, 39-46. https://doi.org/10.21913/IJEI.V5I2.612.

Yoshida, H., 2016. Perceived usefulness of" flipped learning" on instructional design for elementary and secondary education: With focus on pre-service teacher education. International Journal of Information and Education Technology, 6(6), p.430.

Zhang, N., & Yi, A. (2021). The Reasons and Countermeasures of Chinese College Students' unintentional Plagiarism. 2021 7th International Conference on Education and Training Technologies. https://doi.org/10.1145/3463531.3463555.