Questioning learning analytics? Cultivating critical engagement as student automated feedback literacy

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Abstract

For learning analytics to empower students, they must be able to critically engage with the analytics. This is particularly essential in the case of student-facing LA (such as automated writing feedback tools) that require students to make sense of the automated feedback on learning constructs that the students must master, and to act as needed. This paper highlights the importance of critical engagement with a learning analytics tool and a pedagogic design for its implementation with students. It uses student interaction data to demonstrate that students possess different levels of skills to meaningfully engage with the automated feedback and discusses ways to enhance their critical engagement with learning analytics. The work will inform how learning analytics tools can embed critical interaction design to provide its users with increased agency.

CCS CONCEPTS

• **Applied computing~Education~Interactive learning environments** • **Human-centered computing~Interaction design~Empirical studies in interaction design**

Additional Keywords and Phrases:

learning analytics, critical engagement, automated feedback literacy, writing analytics, impact, pedagogy, design, student artefacts, human-centered approach

ACM Reference Format:

First Author's Name, Initials, and Last Name, Second Author's Name, Initials, and Last Name, and Third Author's Name, Initials, and Last Name. 2018. The Title of the Paper: ACM Conference Proceedings Manuscript Submission Template: This is the subtitle of the paper, this document both explains and embodies the submission format for authors using Word. In Woodstock '18: ACM Symposium on Neural Gaze Detection, June 03–05, 2018, Woodstock, NY. ACM, New York, NY, USA, 10 pages. NOTE: This block will be automatically generated when manuscripts are processed after acceptance.

1 Introduction

Learning Analytics (LA) emerged with bold promises to optimise learning and reshape education [1]. However, while there are examples of successful LA implementations, a large proportion of LA studies are still exploratory, demanding more evidence for substantive end results and outcomes of change [2]. This can be attributed to a number of policy and practical issues across institutions. There are reported struggles in the adoption of LA in terms of data quality and access, socio-technical infrastructure, data ownership and privacy, organizational culture, and staff expertise [3]. LA comes under scrutiny from educational researchers, who debate its real world impact on classrooms and students, and

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highlight practical problems those implementations come with. These include the potential that black box systems may diminish informed decision-making, that they deprofessionalize and reduce understanding of educational constructs with narrow views of learning contexts, that they promote performativity and surveillance culture, and perpetuate social inequalities, particularly as students are not the primary beneficiaries of LA systems [4]. Additional concerns related to generalizability and relevance of research to actual practice also hinder the potential impact of LA [5].

A key conversation in recent years has centered on increasing the *impact* of learning analytics [2, 5, 6]. One strategy is to adopt a human-centered approach to LA where the system characteristics are "carefully designed by identifying the critical stakeholders, their relationships, and the contexts in which those systems will function" [7]. This approach enhances interactions that end users such as teachers and students have with LA systems, by designing the systems to address those user needs. By helping users engage meaningfully with LA in a critical fashion, bringing them front and center rather than being tool/tech-centric, we can make the best use of the rich set of LA resources that positively impact learning [6]. This can bring about better uptake of learning analytics among students and educators in 'authentic classroom practice' [8] and help attain the intended outcomes of LA.

In this paper, we employ a human-centered approach to tackle a specific problem: the need for critical awareness and interaction with learning analytics. First, we explain the need for critical engagement by highlighting several interconnected issues it can tackle. The issues we discuss range from black-boxing, imperfect analytics, and the lack of explainability of algorithms and artificial intelligence systems, to the required relevant skills and capabilities of LA users when dealing with such advanced technologies. We note that it is imperative for users to engage with LA *critically* in a meaningful way and are encouraged to exercise the agency to do so. However, we also note the under-researched area of studying how users *actually* engage with learning analytics critically in real-world settings. There are no in-depth studies examining user observations, or the analysis of artefacts from students and teachers when interacting with LA systems, beyond simple usability tests. In the next section, we contribute to this knowledge gap by looking into empirical data from authentic classroom artefacts where students use a LA tool by expanding on a specific case of automated writing feedback. We explore why critical interaction and questioning of learning analytics systems should be encouraged among students, and introduce a deliberate task design for critical LA interaction. We then provide illustrative examples of students' critical engagement (and lack of), and discuss the findings and implications.

2 Why critical ENGAGEMENT

Learning analytics (LA) applications target a multitude of users, including: administrators, policy makers, educators and learners, for the purposes of understanding learning processes and optimising them. Of particular interest in the LA community are tools and technologies that directly support and engage with students as end users, commonly referred to as *student-facing LA* [9, 10]. These systems provide students with more control over their learning, which if designed and deployed effectively, can intrinsically motivate them towards success [9, 11]. Common examples are student-facing dashboards that report learning activities and interaction data, and tools that make educational recommendations and/or provide automated feedback.

However, LA dashboards have been criticised for focusing too much on merely making learners aware of data, but with too little focus on the actions they might take from this feedback [12]. In addition, students may vary in their capability to interpret, make sense of, and use the analytics for learning [13]. These issues are true of relatively simple dashboards which display typical summary data from system logs capturing visible student learning activity. They are compounded by more complex models both due to issues of 'algorithmic literacy', and the potential black-box nature of algorithmic systems in artificial intelligence gives rise to issues in fairness, accountability, transparency and explainability (FATE) [14, 15], which may obscure important information needed by users to make informed decisions.

Critical issues of power have been highlighted when complex LA systems are introduced to educators and students who lack the ability to understand the underlying data analytics but are bound to act on the results, and made liable for not doing so [16]. Since "raw data is an oxymoron" [17], that is, data - including about learning - is curated, crafted, and used by humans to represent particular things in contexts, a critical lens is needed in probing and holding accountable LA interpretations and outputs.

Additionally, LA comes with inherent imperfections in computational models which require careful consideration of the pedagogical design when introduced to students in order for it to be embraced as an opportunity for learning to learn [18]. Indeed, analytics are proxies and indicators of constructs, and LA is somewhat limited in terms of what data can be accurately captured from complex learning activities [4, 16, 19]. Consequently, the *contexts* in which LA occur and how they are made sense of and interpreted by learners are important; data is represented and interpreted in particular contexts, to particular actors, with a range of possible - intended or unintended – outcomes [13, 20].

We therefore emphasize that critical engagement with learning analytics is an essential analytical skill when working with student-facing LA tools. We define critical engagement with LA as *"the act of questioning engagement with data, analytics and computational tools with an understanding of its limitations and assumptions, alongside the analytical ability and agency to challenge its outcomes when necessary"*. Such critical interaction enables students to understand the engagement between their learning, and learning analytics as one of a number of technological tools at hand for them. Central to this view are four key claims, that:

1. **Critical engagement with learning analytics is fundamental for agency because it is activity-oriented, targeted at *doing* learning**. Our tools, including dashboards, should reflect this need for critical engagement through activity-oriented design for critical awareness and reflection, aiming to develop student cognitive, behavioural or emotional competences [12], to build their agency.
2. **Critical engagement is a metacognitive capacity that both demonstrates and builds student understanding,** and therefore students must be able to, and should be encouraged to, question analytics (while its absence may indicate poorer understanding of both data and learning constructs). New forms of feedback that are different to what humans are used to receiving have emerged, which require additional critical skills for interpretation and application. Just as the emergence of AI in other contexts provokes debate about what makes us 'truly human' and how we should relate to machines, the emergence of AI-powered feedback adds new dimensions to the concept of what 'good feedback' looks like, offering opportunities for timeliness, specificity, and augmentation of human intellect, as well as risks.
3. **Critical engagement is particularly important given the inevitable imperfections of models, as one lens - albeit a dirty lens - onto learning.** Learning constructs are represented through proxies that can be captured through data, these are curated, constructed, represented, and do not present a complete view of learning (hence a dirty lens). While there is a general tendency to associate automated tools for accuracy, we note that they are bound by imperfections and biases in algorithms - Imperfectness that is inherent in measurements and machine understanding can sometimes lead to incorrect feedback. Black box systems can reduce agency by obscuring important model features and their implications, from students, expert teachers, and indeed research transparency.
4. **Critical engagement requires design for learning -** including explicit consideration to the ways in which LA are integrated into, and exposed to critique from, the learning task - plays an important role in improving both learning and the use of analytics for learning. Contextual factors affect how data is captured, presented and used by the user, and these go well beyond immediate tools such as dashboards, to wider systems of feedback, course materials, peer-interaction structures and so on [21]. The learning task is a central piece of this context [6]. The significance of design for learning is well established in LA [20, 22, 23].

3 Our approach

While the need for critical engagement with learning analytics is clear, how it can be enabled and facilitated among students requires careful consideration. Students possess varied levels of personal skills and hence, some of them require more guidance in developing these additional capabilities to work with advanced LA systems. They should be empowered with the agency to question the analytics and not feel forced to accept its results at face value. The ability to decline the use of LA results and not being held accountable for the choice has indeed been claimed a necessity by Knox [16], who argues that LA might do the opposite of empowering teachers and students by making them bound to act on results, with liability for not doing so. Hence, our approach intends to place the power of data back with students when they are working with LA tools, using a pedagogical design grounded in both theory, and existing practices.

We draw on the theory of literacies as socio-material practices to imply that LA tools do not exist by themselves and are emergent in relation with other people and things in their contexts [24]. Based on this, we explore student engagement with the material tools in feedback (their assignments, rubrics, cover sheets, and the learning analytics tool providing automated writing feedback as a part of this) in our current study. We capture not just the interactions with the automated feedback tool, but also students' interactions with the material artefacts designed within the learning context. These tools are both digital and non-digital, however a complexity in prior LA research is that much work focuses on constrained digital interaction within a particular learning environment (notably, MOOC platforms), and thus does not have access to wider material resources used, and the reasons for this use. This approach addresses the need to investigate how LA tools mediate and are mediated by their context of use.

4 The case of automated writing feedback

With an increasing use of learning analytics and artificial intelligence (AI) techniques in educational practice, there comes a responsibility to understand how the nature of feedback could change from what humans are capable of providing. In the current study, our focus is on writing analytics [25, 26], in which tools providing automated feedback have been developed for the purpose of aiding writing improvements among learners. AI-based 'reading' and 'annotation' offers relentlessly consistent annotation of text, at a speed, scale and granularity that humans cannot provide. However, since writing is a complex contextual phenomenon and machines are not intelligent enough to comprehend texts completely like humans (at least, not yet), such automated feedback tools target specific features of writing [27]. These include spelling and grammar, rhetorical structures, linguistic indices like lexical diversity, syntactic complexity, cohesion, semantic similarities, etc. [26].

The writing analytics tool that is of interest in the current study is called 'AcaWriter'[1], which automatically identifies rhetorically salient structures in writing using natural language processing. The tool provides contexualised automated writing feedback adapted to specific genres of writing as defined by instructors in addition to a report highlighting rhetorically salient structures that were automatically identified by the tool; for details see [28]. AcaWriter feedback on a sample piece of academic writing is shown in Figure 1.

[1] AcaWriter is available open-source for other institutions to host. For details, see https://cic.uts.edu.au/open-source-writing-analytics/

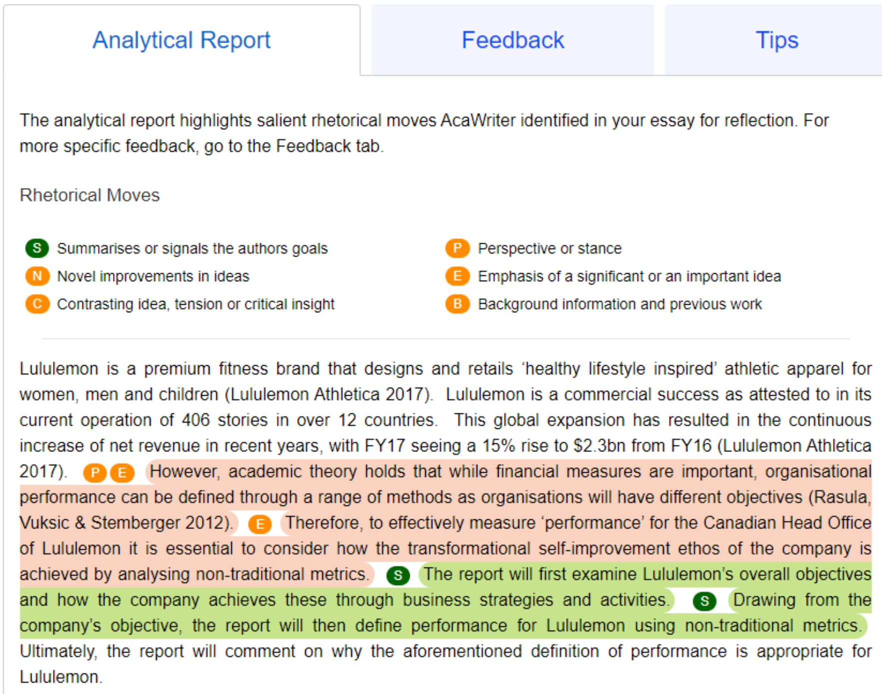


Figure 1: Sample rhetorically salient sentences highlighted by AcaWriter for automated feedback

The tool has been implemented and evaluated across different disciplines and types of writing genres in higher educational classrooms, with findings showing a positive influence in students' writing and their understanding of writing structures [20, 28, 29]. However, there are also noted challenges in how the tool can be effectively used in classroom practice. While feedback from AcaWriter is designed to address structures in writing that proficient writers are adept at identifying, the tool's analysis is based only on the linguistic properties of the text that it can identify. Such is the complexity of writing that feedback from the tool is guaranteed to be imperfect, due to missing contextual knowledge that a human marker would have, a focus on a particular set of features, and imperfections in the detection of those features (We would note of course, that human feedback is far from perfect as well, but in other ways). When providing feedback, AcaWriter provides a cautionary warning to users highlighting the possibility that the tool might wrongly identify a rhetorical structure and students should always use their human judgement to make decisions when responding to feedback provided – see Figure 2 for a screenshot of the message.

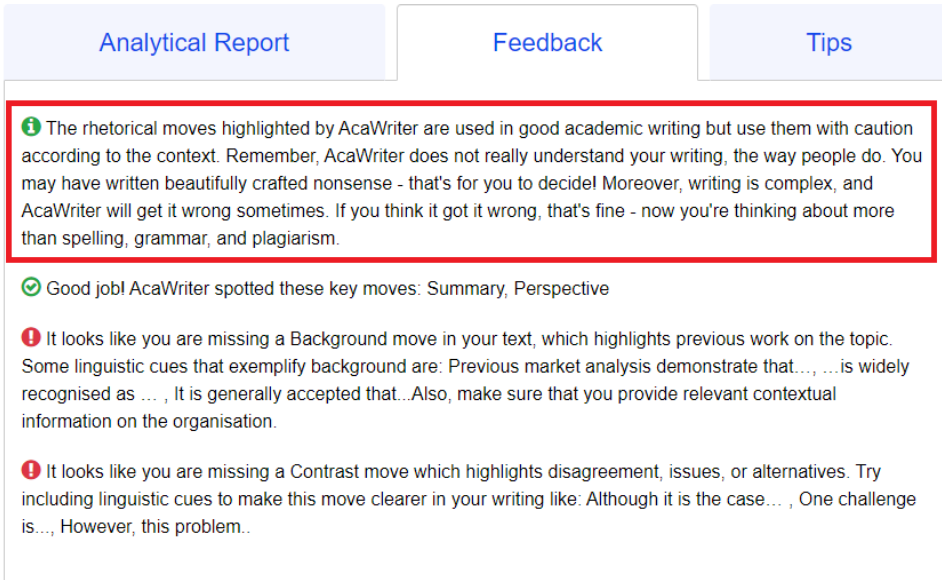


Figure 2: Warning message from AcaWriter along with the feedback messages

The tool hence provides an opportunity for users to disagree with automated feedback explicitly in its design. However, as noted previously, the skills and capabilities to effectively do so, which we call 'automated feedback literacy' [30] is not a given among students. They need additional guidance and scaffolds to critically interact with the automated feedback, which we discuss in the rest of the paper.

4.1 Pedagogic Design

In this section, we explain how critical engagement with LA was mediated through design. The design embedded the usage of AcaWriter in the classroom by *augmenting* existing high quality pedagogical practice [31], rather than replacing it. As part of a pedagogic intervention that was co-designed with instructors, students had to work on improving a draft of their writing using a combination of both automated and peer feedback before final submission, thereby learning revision skills and developing automated feedback literacy in the process. Note that the automated feedback from AcaWriter was already aligned with the instructors' assessment criteria based on a contextualizable learning analytics design model [20] for better uptake and constructive alignment with the curriculum. In the pedagogical design, students were provided with materials to support critical automated feedback engagement which includes instruction on (1) where to get automated feedback (2) how to use the feedback (and discuss it), and (3) when not to use the feedback. Our aim was for students to use AcaWriter as one tool in their toolkit to develop the targeted skill around rhetorical moves. In addition to AcaWriter feedback, students also learned to work with feedback from Grammarly, Turnitin and their peers, but in the interest of the current topic, here we shall discuss students' automated feedback literacy with respect to AcaWriter feedback only.

To facilitate students engaging with automated feedback from AcaWriter critically, they were provided with an additional scaffolding (prompts) as part of their self-evaluation exercise (SEE) – refer Figure 3.

Self-Evaluation Exercise (SEE) prompts for rhetorical moves using AcaWriter

1) Upload your draft report to **AcaWriter**
2) Download and print the PDF showing the AcaWriter feedback on your report
3) Print and review the **Acawriter feedback. Do you agree with the feedback given? Why/ Why not?**
4) On the printed copy of your report (that shows the AcaWriter Feedback), use highlighters and comments to add to the feedback by showing where your report use the following **rhetorical moves**. You should submit this report.

NOTE: AcaWriter will be able to identify most of these rhetorical moves, but not always! It is important to use your (honest) human judgement too.

Organisational analysis

Where does your report provide contextual information about the organisation's objectives, strategy, structure and activities?

Defining performance

Where does your report provide your **perspective [P]** about how to define performance or success for the organisation?

Where does your report **provide emphasis [E]** to highlight the most important aspects of performance for the organisation?

Justification of your definition of performance

Where does your report provide convincing, persuasive justifications for your definition of performance by proposing **novel [N] or critical insights, contrasting ideas or tension [C]**?

Where does your report justify your definition of performance with reference to **background information** or **previous work [B]**?

Written communication

Where in your report do you use appropriate **summary statements [S]** to signal the content, sequence and goals of the report?

5) Spend some time working on the soft copy of your report in the AcaWriter tool, adjusting your report and re-run the AcaWriter analysis. What effect did your changes have in on the feedback from AcaWriter?
6) After using Acawriter what changes did you/will you make to your report?

Figure 3: Self-evaluation exercise prompts for AcaWriter feedback

This material designed for critical engagement involved the following tasks:

- Answer prompts on whether they agreed with the automated feedback
- Explain the rationale behind why they agreed or disagreed with the automated feedback
- Critically analyse the automated feedback by annotating the tool's highlights of automatically identified rhetorical structures, and noting down any agreements and disagreements with the feedback provided.
- Articulate how the feedback was applied and what kind of changes were made in the writing in response to it.

Note that the prompts do not ask students to provide feedback on the tool (similar to a satisfaction, usability or usefulness survey), but they engage students to learn about their writing, and the tool, and the interaction between the two. The mediating artefact of the documents (submitted as cover sheets) provide us a lens into this engagement.

Analysis of student engagement with automated feedback helps us study the 'automated feedback literacy' of students [30]. 'Feedback literacy' has been recognized recently as a key academic skill for students [32, 33]. By using prompts as scaffolds, we encourage students to take a closer look at the feedback and develop their automated feedback literacy. When students respond to these prompts, they record their thinking process, which otherwise would not have been made visible when engaging with automated feedback.

4.2 Study context

Study participants are students from an undergraduate accounting subject in a higher educational institution. The entire cohort comprised of 405 students with a mix of native and ESL speakers. Their instructors co-designed with LA researchers a pedagogic intervention using automated feedback from AcaWriter to improve their writing skills [8, 20]. In the specific assignment, students had to write an essay on defining performance for organisations. In addition to their disciplinary writing, the assignment also constituted a self-evaluation exercise (SEE) facilitating critical engagement with AcaWriter feedback along with other forms of feedback on their drafts. Students submitted these completed SEE sheets in hard copy format to instructors along with their writing assignments for marking. Since there was no electronic submission required by the instructor for this assignment, the activity was done on paper. A sample SEE sheet section where students answer prompts on automated feedback is shown in Figure 4. Students were asked explicitly to apply their human judgement while using the AcaWriter tool for self-evaluation; the prompts provided to students to engage with automated feedback aided this process by acting as scaffolds.

5 ANALYSIS

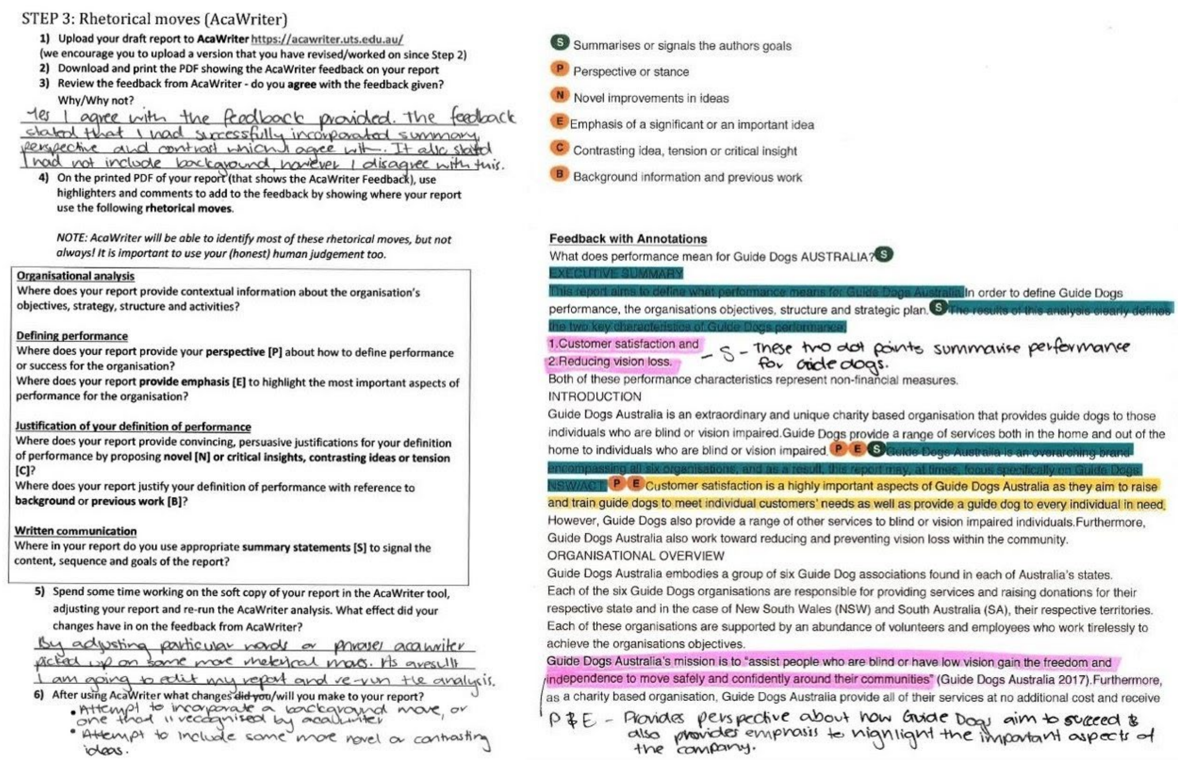
SEE sheets from 114 students were collected from instructors in paper format (based on their availability), scanned, and transcribed for analysis. Thematic analysis was used for themes emerging from student responses to the scaffolding prompts. From students' responses to *prompt 3*, their agreement with automated feedback from AcaWriter was coded manually as one of the following categories:

1. Agree: If they completely agreed with the feedback, without any critique of the feedback provided. Example: *"Yes, I agree with the feedback as my report lacked Background information so I made changes to fit this."* - Student 79

2. Disagree: If they did not agree with the feedback provided, expressing some form of rebuttal to the feedback provided. Example: *"I do not agree with the feedback given because some sentences about background, emphasis and perspective are not highlighted by the software."* - Student 50

3. Neutral: If they agreed with some parts of the feedback and not others, or agreed to some extent with rebuttal to few instances of feedback. Example: *"The AcaWriter report points out some of the errors and strengths of my report of which I agree with some and disagree with others. Concerning the highlighted company's objectives, the report indicates that my points are not clear, which I heartily agree. The goals and aims of the company are not explicitly illustrated in the report. Additionally, the report is right in identifying my emphasizing points on the company's definition of performances. The report also highlights correctly the areas where I have justified my description of performance either using previous work, novel or the critical insights and tension."* - Student 68

4. NA: Did not answer the question



STEP 3: Rhetorical moves (AcaWriter)

1) Upload your draft report to **AcaWriter** https://acawriter.uts.edu.au/
(we encourage you to upload a version that you have revised/worked on since Step 2)
2) Download and print the PDF showing the AcaWriter feedback on your report
3) Review the feedback from AcaWriter - do you **agree** with the feedback given? Why/Why not?

Yes I agree with the feedback provided. The feedback stated that I had successfully incorporated summary, perspective and contrast which I agree with. It also stated I had not include background, however I disagree with this.

4) On the printed PDF of your report (that shows the AcaWriter Feedback), use highlighters and comments to add to the feedback by showing where your report use the following **rhetorical moves**.

NOTE: AcaWriter will be able to identify most of these rhetorical moves, but not always! It is important to use your (honest) human judgement too.

Organisational analysis
Where does your report provide contextual information about the organisation's objectives, strategy, structure and activities?

Defining performance
Where does your report provide your **perspective [P]** about how to define performance or success for the organisation?
Where does your report **provide emphasis [E]** to highlight the most important aspects of performance for the organisation?

Justification of your definition of performance
Where does your report provide convincing, persuasive justifications for your definition of performance by proposing **novel [N] or critical insights, contrasting ideas or tension [C]**?
Where does your report justify your definition of performance with reference to **background** or **previous work [B]**?

Written communication
Where in your report do you use appropriate **summary statements [S]** to signal the content, sequence and goals of the report?

5) Spend some time working on the soft copy of your report in the AcaWriter tool, adjusting your report and re-run the AcaWriter analysis. What effect did your changes have in on the feedback from AcaWriter?

By adjusting particular words or phrases acawriter picked up on some more rhetorical moves. As a result I am going to edit my report and re-run the analysis.

6) After using AcaWriter what changes ~~did you~~/will you make to your report?
- Attempt to incorporate a background move, or one that is recognised by acawriter
- Attempt to include some more novel or contrasting ideas.

S Summarises or signals the authors goals
P Perspective or stance
N Novel improvements in ideas
E Emphasis of a significant or an important idea
C Contrasting idea, tension or critical insight
B Background information and previous work

Feedback with Annotations
What does performance mean for Guide Dogs AUSTRALIA? S
EXECUTIVE SUMMARY
This report aims to define what performance means for Guide Dogs Australia. In order to define Guide Dogs performance, the organisations objectives, structure and strategic plan. S The results of this analysis clearly defines the two key characteristics of Guide Dogs performance.
1.Customer satisfaction and
2.Reducing vision loss.
– S – These two dot points summarise performance for guide dogs.
Both of these performance characteristics represent non-financial measures.
INTRODUCTION
Guide Dogs Australia is an extraordinary and unique charity based organisation that provides guide dogs to those individuals who are blind or vision impaired.Guide Dogs provide a range of services both in the home and out of the home to individuals who are blind or vision impaired. P E S Guide Dogs Australia is an overarching brand encompassing all six organisations, and as a result, this report may, at times, focus specifically on Guide Dogs NSW/ACT. P E Customer satisfaction is a highly important aspects of Guide Dogs Australia as they aim to raise and train guide dogs to meet individual customers' needs as well as provide a guide dog to every individual in need. However, Guide Dogs also provide a range of other services to blind or vision impaired individuals.Furthermore, Guide Dogs Australia also work toward reducing and preventing vision loss within the community.
ORGANISATIONAL OVERVIEW
Guide Dogs Australia embodies a group of six Guide Dog associations found in each of Australia's states. Each of the six Guide Dogs organisations are responsible for providing services and raising donations for their respective state and in the case of New South Wales (NSW) and South Australia (SA), their respective territories. Each of these organisations are supported by an abundance of volunteers and employees who work tirelessly to achieve the organisations objectives.
Guide Dogs Australia's mission is to "assist people who are blind or have low vision gain the freedom and independence to move safely and confidently around their communities" (Guide Dogs Australia 2017).Furthermore, as a charity based organisation, Guide Dogs Australia provide all of their services at no additional cost and receive
P & E – Provides perspective about how Guide Dogs aim to succeed & also provides emphasis to highlight the important aspects of the company.

Figure 4: **Sample SEE sheet section on AcaWriter feedback submitted by a student**

From the next prompt that asked students about the effect that AcaWriter feedback had on their writing after they spent some time working on their reports from AcaWriter analysis, and the following prompt that asked students to report on the changes they have made/ will make to their report after using AcaWriter, their engagement with automated feedback was studied. Student responses to *prompts 5 and 6 in Figure 3* were analysed to study two forms of engagement: i) the extent to which students understood AcaWriter feedback and ii) how they applied the feedback to improve their writing. Together, they were coded as one of the two categories described below:

1. Deep: If they demonstrated an understanding of how AcaWriter picks rhetorical structures to provide feedback and/ or applied the feedback to make significant revisions.

Example: *"The changes that were made created more areas of background information as well as greater emphasis of ideas. Once completed, the feedback determined that all of the key rhetorical moves had been addressed. This allowed the report to be more analytical to provide a greater justification of the definitions of performance.*
1) Many changes were made by re-wording some sections to create more emphasis. This occurred particularly within the strategy section providing greater emphasis of the importance of the strategies that are employed by [the company] in allowing the Company to achieve its overall objectives. 2) Stronger background information was provided within the areas that defined performance. This was to provide a greater justification of the definitions of performance, particularly within the innovation and environmental sustainability section, which now provide a greater justification of the definition, rather than just a description. 3) In reformatting the sentences to meet the requirements of the rhetorical moves, the overall persuasiveness of the definitions of performance was improved. This was done to provide a stronger link between the company's recognition of performance and the achievement of its mission, to justify why the said definition of performance is important." – Student 60

2. Shallow: If they failed to exhibit a deep understanding of AcaWriter feedback by critically engaging with the feedback to make considerable revisions.
Example: *"There is nothing much that changes as AcaWriter managed to detect most of the aspect.*
1) More summary statements presented as it lacks initially. 2) I will provide more critical ideas." - Student 73

6 Results and Discussion

From the data coded from SEE sheets, a cleaned dataset was created by removing the inconsistencies and missing data (unanswered NAs). Preliminary results from the analysis of this cleaned data consisting of 105 records are discussed next.

6.1 Individual summary

With regards to agreement with automated feedback, 77 agreed, 21 disagreed and 7 out of the 105 students had a neutral stance on automated feedback. We also saw more than half (55 students out of 105) showing shallow engagement with automated feedback.

6.2 Relationship between agreement and engagement with automated feedback

To compare how students who agreed, disagreed or had a neutral stance with automated feedback fared in terms of engagement with the feedback, we show the proportions of students' engagement categorised by agreement in Figure 5.

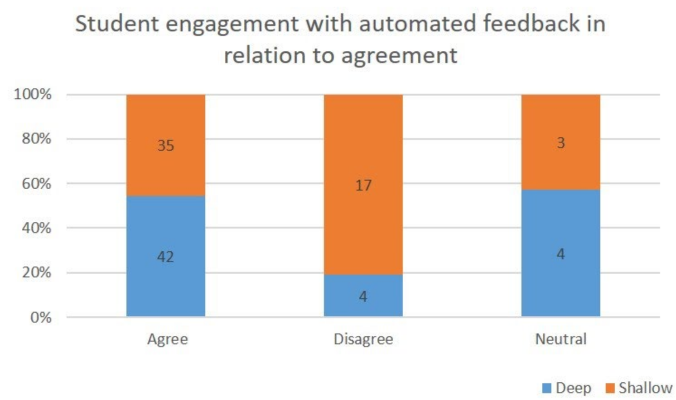


Figure 5: Proportions of students with deep and shallow engagement with AcaWriter feedback categorised by agreement categories

55% of students in the group who agreed with automated feedback from AcaWriter demonstrated deep engagement with the feedback and 45% showed shallow engagement. In the group of students who disagreed with the feedback, most students (81%) demonstrated shallow engagement. In the neutral agreement group, about 57% showed deep engagement with the automated feedback. A statistically significant association between feedback engagement and agreement was found in a chi-squared test: $\chi2$ (2) = 8.6, $p < .05$. Whether students agreed or disagreed with the automated feedback seemed to have an effect on how deeply they engaged with the feedback.

6.3 Relationship with marks

To study the potential impact of student engagement with automated feedback using more tangible outcomes, marks that measured student performance in this writing assignment were obtained from the instructors. Based on the assessment criteria for business reports, the assignments were scored for written communication in the range of 0 to 30 by the instructors and tutors, and these marks contributed to overall credits for the subject. The difference in the marks scored by students belonging to the three groups of agreement with automated feedback (agreed, disagreed or maintained a neutral position) and the two groups of engagement (deep, shallow) are discussed next.

Students who disagreed scored slightly higher ($M = 22.81$, $SD = 3.33$, $N = 21$), in comparison to students who agreed with the feedback ($M = 22.04$, $SD = 4.17$, $N = 77$) and the neutral group ($M = 20.79$, $SD = 2.23$, $N = 7$). However, one way ANOVA found no significant difference in mark across the groups, $F(2,102) = .74$, $p > .05$. Hence, whether students agreed or disagreed with the automated feedback from AcaWriter was not related to their writing performance.

In terms of student engagement, differences were found in student marks between the shallow and deep engagement groups based on their understanding and application of automated feedback from AcaWriter. Students who demonstrated deep engagement with AcaWriter feedback scored higher ($M = 23.33$, $SD = 3.29$, $N = 50$) than students who had shallow engagement ($M = 21$, $SD = 4.14$, $N = 55$). A significant difference was found between the groups in a Welch two sample t-test: $t(101) = 3.21$, $p < .005$, with a medium observed effect (Cohen's $d = -.62$, 95% CI [0.22, 1.02]). This suggests that students' level of engagement with feedback relates to their writing performance, and supports the case for improving students' automated feedback literacy.

6.4 Annotation samples

Assessment artefacts provide both a lens onto student thinking, and a tool to support and make visible that thinking for students and teachers. The study of student artefacts helps understand student interaction and their thought process when engaging with automated feedback. They might also help uncover their reasoning behind the acceptance or rejection of certain parts of automated feedback. This can aid our understanding of students' level of critical engagement with automated feedback. Therefore, in addition to the quantitative analysis discussed above, we present illustrative examples of student annotations on AcaWriter feedback.

In the sample pages of annotations in Figure 6, we observe highlights and comments that students who agreed/ disagreed with the feedback made on top of AcaWriter highlighting and rhetorical moves.

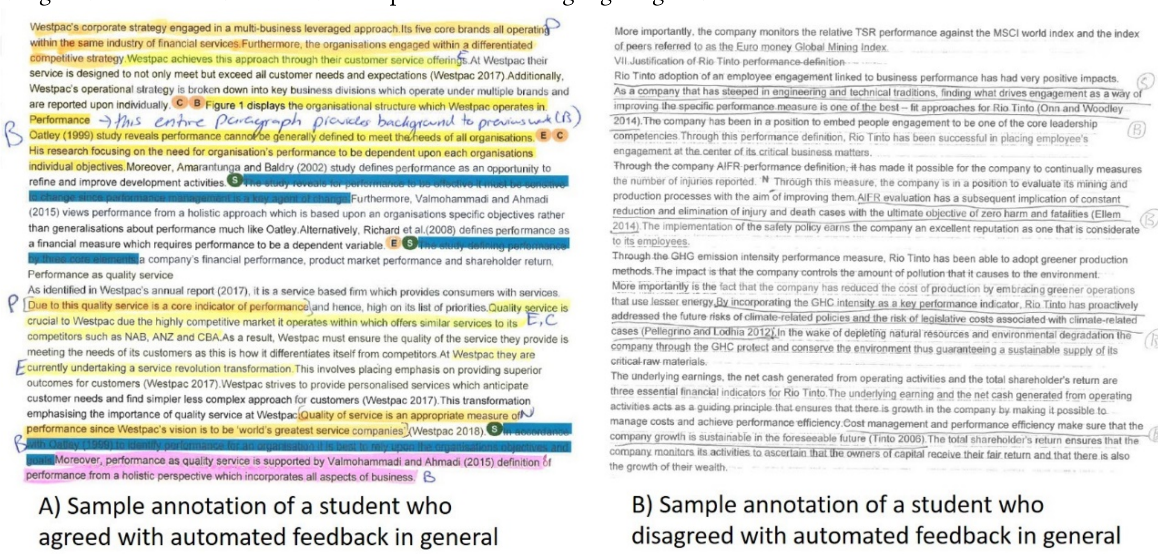
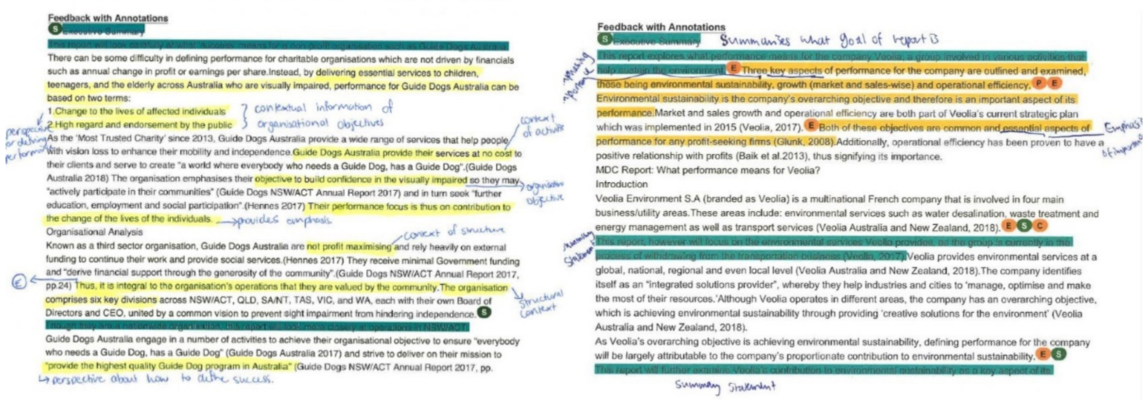


Figure 6: Sample student annotations to examine agreements

In the first sample (A), we see that the student added more rhetorical moves, adopting the notations that AcaWriter uses to denote moves such as B (Background), P (Perspective) and E (Emphasis), and a comment on how a move applies to an entire paragraph. This student had agreed with automated feedback in the earlier prompt. Even though some rhetorical moves are missed by the tool, the student still recognises the usefulness of the tool and agrees with its feedback on the identified parts, likely because they understand the limitations of the LA tool and are able to apply the feedback critically. In the second sample (B), the student has noted some missed rhetorical moves, again in the same format that AcaWriter uses to denote rhetorical moves. This student however disagreed with automated feedback, and this could be related to the fact that the tool did not pick up any of the rhetorical moves that the student believed to be present in their writing. This could be an explanation for our previous results that showed that students who demonstrated shallow engagement with the automated feedback tended to disagree with the feedback more (31%) in comparison with the disagreement percentage in students showing deep engagement (8%).

In Figure 7, we show the sample pages of annotations of students who demonstrated shallow / deep levels of student engagement in their responses to prompts. Sample C comes from a student whose response to prompts was coded for ‘deep’ engagement with automated feedback. This student has recognized more rhetorical moves in their writing in addition to what the tool identified, and highlighted them similar to the tool’s highlighting. They have also used the tool’s notations to represent emphasis (E), and added comments to capture other rhetorical moves such as context, which are relevant to the assignment but not included in the tool’s analysis. On the other hand, the student’s annotations in sample D show that they only repeated what the tool identified in comments, and have not added any new rhetorical moves - note that this student’s response to the prompts was coded to be indicative of shallow engagement.



C) Sample annotation of a student who showed deep engagement with automated feedback

D) Sample annotation of a student who showed shallow engagement with automated feedback

Figure 7: Sample student annotations to examine engagement

The analysis of annotated sheets help inform the preceding coding of agreement with automated feedback. They provide reasoning that can explain the thinking behind why a student could have agreed/ disagreed/ had a neutral stance towards automated feedback based on their critical engagement. They also help enlighten our views on how the student actually engaged with automated feedback, which can be studied against what they self-reported earlier. This kind of annotation thus provides evidence of the significance of these artefacts in understanding how the student’s work mediates and is mediated by the range of tools available to them, and the potential of analysis of wider task artefacts in understanding engagement with LA tools. It is interesting to see many students adopting the tool’s symbols and notations for their own annotations when there was no explicit instruction to do so. By providing a common language (in the form of symbolic notations and highlights), the tool has aided students’ thinking about rhetorical moves when working on their own writing.

7 Limitations and future work

As with any human coding, there were problematic aspects in interpreting student responses to the prompts. We noted that students demonstrated varied levels of understanding and incorporation of AcaWriter feedback into their revisions. During coding, we were able to recognise instances that clearly fell into a certain category (deep or shallow engagement), but a few others were hard to distinguish, particularly if their wordings were not explicitly indicative of their understanding. The following examples of students' comments on AcaWriter were hard to code conclusively as 'deep' or 'shallow' (but since they demonstrated possible deep engagement which was not elaborated, they were provided the benefit of doubt and coded as 'deep'):

- *"1) Added background reference to [organisation]- (B) achieved 2) Increased justification to 'performance' definition - more (N) and (c) appeared. 1) Greater reference to background/ previous work. 2) Improved justification to [author]'s(1999) "performance" definition. 3) Increased reference to academic sources." - Student 30*
- *"AcaWriter recognised where I made changes and I was able to integrate all rhetoric moves into my report. 1)found more academic relevant articles 2) rearranged sentences as to improve structure 3) Rephrase the last section since no moves were highlighted despite editing it" - Student 3*

If students do not elaborate on their interactions and application of automated feedback in their response to prompts, it poses a challenge to code their text for critical engagement. Furthermore, there were differences even within the deep and shallow categories of engagement. While few students demonstrated a good understanding of automated feedback and disregarded its suggestions if appropriate, few others brought about better revisions in their writing although they did not apply the automated feedback properly. A finer-grained coding scheme could be developed to capture this range within deep and shallow understanding. Moreover, this coding scheme should be validated with interrater reliability involving multiple coders to generalize findings. More detailed analysis of student annotations can unveil different types of student engagement and thinking when interacting with automated feedback. These can help expand research on automated feedback literacy, allowing conclusions to be made from individual differences among students. The manual work behind the coding is also time and labour intensive as student submissions were submitted on paper following the usual practice of instructors. Future versions of AcaWriter could offer an enhanced user interface with prompts that enable easier online data capture from student annotations agreeing/disagreeing with the feedback. Future work can also include additional think-aloud strategies to capture the cognitive processes behind student engagement and application of automated feedback.

8 Conclusion

This paper argues for the importance of aiding students' critical engagement with learning analytics to address the issues of black-boxing, poor explainability, lack of context and imperfection in algorithms [15]. The argument is based on four claims backed by literature and our empirical work in the current study. By closely aligning learning analytics with learning constructs [21, 23] and encouraging critical engagement *by design*, we can develop students' agency and metacognitive capacity to engage with learning analytics meaningfully [16]. We have presented a pedagogical design to cultivate critical engagement skills among students that can be remodelled for different learning contexts.

We also analysed the quality of student interaction with the automated feedback. Findings showed that students exhibited varied levels of engagement with automated feedback, ranging from shallow to deep engagement. Whether they agreed or disagreed with the feedback did not correlate significantly with final grade, but their level of engagement did have a moderate effect, suggesting the significance of students' automated feedback literacy for learning, and demonstrating the value of analysing artefacts for engagement reflection to support and probe this. Results thus support the need for better (critical) engagement with LA as deep engagement had a significant relationship to student performance. Future related work should target replication and measurement models in this space.

We know from the feedback literacy literature that students struggle with using feedback effectively even when it comes from knowledgeable instructors [32, 33]. The concept of feedback literacy becomes even more important when students are asked to engage with automated feedback with characteristics that are different to human feedback.

Student-facing learning analytics tools should hence consider the confidence and skills of students to engage critically. By recognizing the needs and skills of different students, LA can provide appropriate guidance for students to improve their learning and reach its intended outcomes. Thus, as we understand what feedback literacy may mean in these new contexts, educators must teach students the critical usage of such technologies.

In this paper, we presented a pedagogical design that acts as an enabler for automated feedback literacy. In the design, training for students to develop their critical engagement was enabled using scaffolding prompts in the self-evaluation exercise and the tool's explicit instructions to disagree with the automated feedback if needed. Such deliberate designs of critical engagement with automated feedback open up avenues for students to meaningfully engage with learning analytics. By providing agency for students to either accept or reject automated feedback as necessary, we empower learners to make informed decisions on LA. This enables improved transparency for LA as it provides an opportunity for users to "refuse to be overawed by the process, to understand the tools and techniques, their strengths and limitations, and to use that understanding to improve teaching and learning" [19].

The way the scaffolds are designed provide a different kind of insight into what students are doing with automated feedback and how, which are inaccessible from the tool's log data alone. Such artefacts help us reflect on the tool's actual usage by students as their thinking process is now observed, which otherwise would not have been made visible when engaging with automated feedback. The design abstraction and tasks from the exemplified activity can be translated to other learning analytics contexts for general principles of critical engagement. On the basis of the above arguments and evidence, we conclude that cultivating students' critical engagement with feedback from learning analytics tools should become a normative practice.

ACKNOWLEDGMENTS

We thank the academics who co-designed the writing analytics deployments described in this paper: Nicole Sutton and Raechel Wight. The paper draws from data reported in the PhD thesis: A. Shibani, 2019.

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