Attentional and cognitive processing of analytics visualisations: Can design features affect interpretations and decisions about learning and teaching?

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There has been an increasing demand for course-level learning analytics to inform design improvements and interventions. While there has been an increasing research and development focus on dashboards to facilitate this, less has been done to investigate the impact of design features on optimising the interpretation process when translating learning analytics into actionable interventions and design changes. In this paper, I assess the effect of two prominent design features on the attentional and cognitive processes when using learning analytics at the course level. Emergent thematic analysis revealed response patterns suggesting systematic effects of three design features (course-only data, course- versus school-level data, course-only data with learning events marked) on the interpretive patterns, proposed actions, and consequential thinking of participants in the study. Implications for future designs of course-level learning analytics dashboards, as well as academic development are discussed.

Keywords: Learning analytics, dashboard designs, visualisations, attention, data literacy.

Introduction

In the Higher Education sector, learning analytics has increasingly gained impact in addressing a range of educational challenges and issues, including student success and retention (e.g., de Freitas et al., 2014). Work in the area of student retention in general has adopted predictive algorithms in application of learning analytics, in conjunction with student demographic variables to predict the likelihood of attrition of students particularly in their first year of enrolment (e.g., Dietz-Uhler, & Hurn, 2013). More recently, there has been an increasing focus on the usability and validity of learning analytics used in the context of enhancing learning and teaching (Gašević, Dawson, & Siemens, 2015; Gašević, Dawson, Rogers, & Gasevic, 2016).

One of the ways in which learning analytics is incorporated into learning and teaching practice is by way of learning analytics dashboards. On the surface, the premise of incorporating learning analytics via dashboards into learning and teaching practice is seemingly simple – make student learning data available and accessible to educators to help them identify areas of improvement for student engagement and learning. This should then help educators make adjustments to their practice accordingly. These changes should subsequently improve educators' pedagogical practice and overall student learning and academic achievement. This theoretical approach is based on the premise that there is a linear, straightforward relationship between data and pedagogical practice decisions that will improve student learning and academic outcomes. In reality, this suggested pathway from making digital data log files available to effective pedagogical action is a simplification of the complexities of implementing such approaches in a university. I argue that there needs to be consideration of complex organisational, educational, and learning factors before the sector sees large-scale benefits of digital data-informed practice.

Various factors have been identified in the literature that impact on the success of institutional implementation of learning analytics, including: technical infrastructure, privacy and ethical policies and considerations, data expertise, research competencies, and culture change in institutional readiness to adoption and strategic leadership (e.g., Duval, 2011; Macfadyen & Dawson, 2012; Pardo & Siemens, 2014; Slade & Prinsloo, 2013). This paper will focus on the impact of specific design features of learning analytics visualisation on the interpretation of the data and will include a discussion of ideas directed at connecting to course-level action enhancements. Thus far, there has been substantial sector-wide progress made in this regard, with research and development focused on providing learning analytics dashboards to educators to equip them with additional tools to inform their learning and teaching practices such as course design and design of interventions to enhance student learning, or to enhance the learning experience. There have been a wide range of dashboards, varying in the nature and range of data presented, the design features, and purposes of use. Examples include those developed at Higher Education institutions. For example: Course signals (Arnold & Pistilli, 2012) -

learning analytics dashboards to enable course instructors to provide real-time feedback to at-risk students, featuring a traffic light system for quick visual indication of whether the student needs help; and Loop Tool (Bakharia et al., 2016) - course-level learning analytics dashboard to enable instructors to improve their learning design, featuring event-marked course analytics. There are also others developed by educational vendors (e.g., Blackboard Analytics, Echo 360 analytics, D2L predictive learning).

While the impact of the pedagogical beliefs of educators on learning and teaching practice has been well-documented (Lumpe, Haney, & Czerniak, 2000; Trigwell, Prosser, & Waterhouse, 1997), the direct influence of pedagogical beliefs for the use, interpretation, and integration of data-informed practice is not as clear. Data in isolation neither allows for valid interpretation and judgement, nor provides an inherent sense of direction of action. According to Mandinach (2012), to best use data to inform learning and teaching practices educators need to apply pedagogical content knowledge (Shulman, 1986). Educators bring to the instructional environment knowledge about how the data can be used to impact pedagogical design practices, and subsequently can provide instruction to affect change in student learning and performance. This ability to translate and transform data to instructional action is called pedagogical data literacy or instructional decision making. In considering pedagogical data literacy for learning analytics, where the potential affordance is more varied than that within the Mandinach applied contexts (i.e., data-driven decision making in schools), I argue for the added critical importance of principles of scientific inquiry (connectivity, inferential, and convergence principles; see Stanovich & Stanovich, 2003 for in-depth discussions of these) and to consider specifically, the unique need for pedagogical content knowledge within the domain of educational technology given the digital data source that is learning analytics.

A manifestation of pedagogical data literacy is educators' capacity to interpret data within their context to inform pedagogical action. Without pedagogical data literacy (not just pedagogical content knowledge, or data literacy in isolation), the educator runs the risk of forming judgements and making decisions on the basis of cognitive biases. If educators' pedagogical data literacy is key in determining the long-term, sustainable practice of using learning analytics to inform learning and teaching practice, how do we design systems and support professional learning of educators to optimise the ethical and intelligent application of learning analytics to enhance course design and student success?

Critical to the use of data to make decisions about learning and teaching strategies is the fundamental role that these cognitive mechanisms play in the processing of the data (information) and the subsequent decisions made for actions. Two primary human information processing factors play an important role in judgement and decision making from data are: (1) attention, and (2) cognitive biases. Attention acts as a gateway for information processing, determining what gets further processing in the brain, and what is selectively ignored from further processing. Attentional resources can be more automatically captured or guided by bottom-up features, such as familiarity of stimuli or physical features of the visual stimuli (e.g., colours, edge, salience of information, motion). Depending on the combined attributes of the visual stimuli, attention biases selection of certain features over others by simultaneously enhancing the neural response to the selected attributes, and attenuating cortical activity to the relatively ignored attributes (Desimone & Duncan, 1995). Bottom-up attention is fast, and guides or primes attentional selection of stimuli for further processing. Attention can also be guided by top-down factors, such as beliefs, intentions, and knowledge (see Styles, 2006 for review). Volitional control, based on expectancy, prior knowledge, and goals guides attention in a top-down manner, and occurs later (Theeuwes, 2010) thus serving to adjust the bottom-up selected features to a limited extent (McMains & Kastner, 2011). Depending on the interaction between the automatic, bottom-up features and more strategic, controlled top-down factors, the attentional selection of prioritised features will guide and limit what gets further processing in the final percept and judgement of the information (Serences & Yantis, 2006). Together, these form the set of neural resources for further processing of the information one is presented with in the world. Kahneman (2003) conceptualises these two forms of attention as *System 1* (fast, automatic, bottom-up) and *System 2* (slow, deliberate, controlled, top-down). When interpreting and making decisions from data, these two systems can operate in parallel, though one process may dominate depending on various contextual factors.

In the case of learning analytics dashboard applications, these features impact on attentional priority through selective attention mechanisms. This subsequently impacts on the nature of interpretation, as well as decisions made for action on the basis of the data visualisations provided. Hence, it is of utmost importance to consider the design features in terms of understanding ways to optimise designs of these dashboards to promote and drive adaptive (not maladaptive) behaviours. In the sector, there are a few prevalent design features that dominate the market for course-level learning analytics dashboards. One is the comparison of a school or department average when providing analytics related to access and interaction activity (e.g., Blackboard Analytics). The other is only the standard course-related data, and more recently, the idea of aligning some learning events on the access and interactions visualisations (Bakharia et al., 2016). The question here is: what is the contribution of these specific design attributes in influencing attentional selection as well as subsequent interpretations and translation of data for action?

The second critical information processing factor is the likelihood of cognitive biases influencing judgement and decision making. According to Kahneman (2003), System 1 thinking includes non-physical feature-based automatic processes such as cognitive biases. Substantial evidence from cognitive psychology reveals that people employ cognitive shortcuts to simplify the processing data for interpretation and decision-making (Tversky & Kahneman, 1981). These sources of bias can be referred to as "heuristics", and are often proposed to be the fast, representative, substitution attributes that come more readily to mind (Kahneman & Frederick, 2002). Typically, these cognitive biases arise as a strategy to reduce cognitive load or effort by simplifying the processing of the information (Shah & Oppenheimer, 2008). This inherent sense of forming intuitive judgements from graphical displays contradicts the complex perceptual and cognitive processes needed to make informed and accurate judgements. This gives a false (intuitive) sense of efficiency in forming judgements quickly on the basis of graphs rather than raw or statistical data stems from reliance on and preference for heuristics or cognitive biases (Meyer, Taieb, & Flascher, 1997). While heuristics are time and cognitive load efficient, they may also lead to systematic and predictable errors (Tversky & Kahneman, 1974). Of these, a common bias that is often perpetuated in learning and teaching practice is that of the representativeness bias (Kahneman & Tversky, 1972) – that is, the tendency for the educator to rely on evaluating the probability that the data reflects features that may be similar to an easily accessible knowledge on the parent population (e.g., knowledge of stereotyped biases, recency in memory). These biased interpretive lens may therefore lead educators to selectively attend to certain types or aspects of data over others, which may then shape their conclusions, and consequently inform their instructional or learning design in less than optimal ways.

The question in the context of dashboard design and academic development here is: are there ways to mitigate this automatic process of cognitive biases towards more deliberate, objective interpretation, judgement, and decision making using learning analytics? Gigerenzer (1991) argues that in complex, less-than-certain contexts, these cognitive biases may be permeable to interventions. Indeed, van Bruggen, Smidts, and Wierenga (1998) demonstrated that well-designed, contextual, decision support systems in conjunction with data presented for decision making in a managerial marketing context resulted in a reduction in the reliance on cognitive biases in decision making. These effects however, are small and depend on the design of the tools in supporting the complex critical thinking processes involved in interpretation and translation of data in making decisions in practice. These suggest that while cognitive biases may be implicit and difficult to mitigate, they are not completely impermeable to change.

The current research:

1. Seeks to investigate the extent to which visualisation factors affect attentional focus and interpretation of learning analytics.
2. Seeks to better understand schemas and attributions educators make when interpreting learning analytics for enhancement of learning and teaching in a setting designed to be close to a naturalistic 'busy academic' scenario.

As this research is broader than the scope of the current paper, I will focus on the main aims and will only report relevant methods and results. The questions of interest to address these aims are whether the visualisation differences affect the interpretive lens which educators employ when processing these graphs in trying to enhance learning and teaching. Are there themes in the interpretation and application that are suggestive of systematic attentional focus and interpretative lens across the three conditions (*Control*: Course-level only; *Event-Marked*: Course-level data with learning events marked; *Comparative*: Course- versus School-average data)? The rationale for addressing these questions is to better understand the information processing of learning analytics data to inform evidence-based designs of future learning analytics dashboards. To test this, I propose an extension of the existing learning analytics cycles to include consequential thinking when placing the educator at the centre of making meaning and designing subsequent actions for learning and teaching (see Figure 1 for extended learning analytics cycle), and promoting metacognitive processing of learning analytics as educators.

Currently, multiple models or cycles for learning analytics exist in the literature, though they typically emphasise the collection of data, followed by some analysis (or interpretation), and followed by action (e.g., Clow, 2012, Chatti, Dyckhoff, Schroeder, & Thüs, 2012). I propose that this addition of consequential thinking before action bridges the gap between data interpretation and action, such that the actions are more likely to be informed by current learning research and deliberate design before implementation and iteration. This final step, consequential thinking, was included in the model to highlight the importance of deliberate consequential thinking and planning as part of the explicit, a priori and iterative learning analytics cycle for learning and teaching, scholarship of teaching and learning (SoTL), or reflective practice. This added step in the learning analytics cycle fits within a design-based research methodology when using learning analytics for learning and teaching or SoTL (Brown, 1992; Reimann, 2006), or that of double-loop learning in reflective practice (Argyris, 2002).

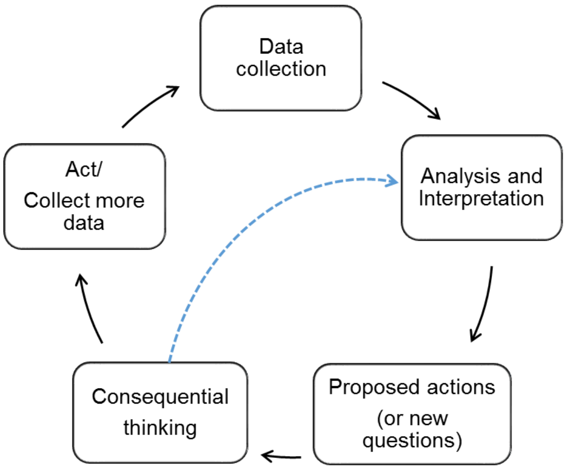

Figure 1. Learning analytics cycle for metacognitive educators. Consequential thinking is where interpretation is reviewed and refined through connectivity and inferential principles. Refinement and iteration continues *throughout* the cycle, with multiple double loops *during* each cycle (as indicated by dotted arrow).

Method

Participants

Participants were academics in a higher education institution from various disciplines, with varying teaching and data use experience. Participants were randomly allocated to one of two conditions: Overperforming course, and Underperforming Course. Relevant statistical tests were performed to test whether the two groups differed on several learning and teaching demographic factors: Academic disciplines, teaching modes, number of years of teaching, number of years of using data for learning and teaching, frequency for using data for learning and teaching, and engagement in learning and teaching practices. Chi-square tests of independence for categorical variables, and Mann-Whitney U tests run for continuous variables based on the small sample sizes per group (*p*s range = .235 - .805). These tests indicated that these groups were equivalent on all the relevant teaching and data-use experience, suggesting that the groups were comparable across the dependent variables of interest. Interestingly, the distribution of academics who self-selected to participate were biased towards the Sciences (n=11 out of 23).

Design

The study comprises a mixed experimental 2 (Between*: Over/ Under- performing course*) x 2 (Within: Scaffolding condition (*Unscaffolded/ Scaffolded*)) x 3 (Within: Visualisation conditions (*Control/ Comparison/ Event-marked*)) research design. In a 2-part online questionnaire, participants responded to a series of questions about their learning and teaching practices, and a set of questions proceeding 3 data scenarios (see Figure 2 for schematic of experimental design). Voluntary informed consent was obtained as per the ethical clearance (GU ref no: 2016/413) in accordance with the National Statement on Ethical Conduct in Human Research. The study was conducted as part of a larger in-person session about course-level learning analytics.

Data Scenarios

The data scenarios comprised three sets of graphs of learning analytics, contextualised within the self-report course characteristics (teaching mode, class level (undergraduate years (1- 4), or postgraduate coursework), and the typical number of students in the course) as determined by the participant. The rationale for this self-contextualisation is to ensure that the course context on which the respondent can draw upon in answering learning and teaching questions is equally familiar for all participants to their own courses, to enable interpretation and application of the data in a context that is relevant for oneself. A defined, pre-set scenario characteristic would vary the extent of familiarity of the individual respondents, hence biasing the academics whose contexts were more similar to the pre-set scenario than those with relatively minimal or less experience.

The three sets of graphs depict three different visualisations commonly used in learning analytics dashboards within the sector at present. They depict access (i.e., log-ins) and interaction activity (i.e., clicks) within the Learning Management System across three visualisation conditions: (1) Control (course level data only), (2) Comparison (own course-level data displayed with the School average data, where 'School' is the collective discipline, such as School of Public Health, where multiple degree/ programs may fall under one School), and (3) Event-marked (course level data only, with learning events marked on the graphs). The course data presented in both the Overperforming and Underperforming group was kept constant to ensure consistency and equity of interpretation potential across groups. The only difference in both groups is the School-level comparison data, where one group was presented with the School comparator line as higher than that of their course (Underperformer), or vice versa (Overperformer). Hence, the control and event-marked graphs were exactly the same for all participants. To minimise the order effects of going from or to an underperforming or overperforming course data, the order of the three graphs were counterbalanced across participants. Figure 3 illustrates an example of the visual graphical stimuli presented in one condition Overperforming group, Compare condition in the unscaffolded condition (background), and scaffolded condition (foreground).

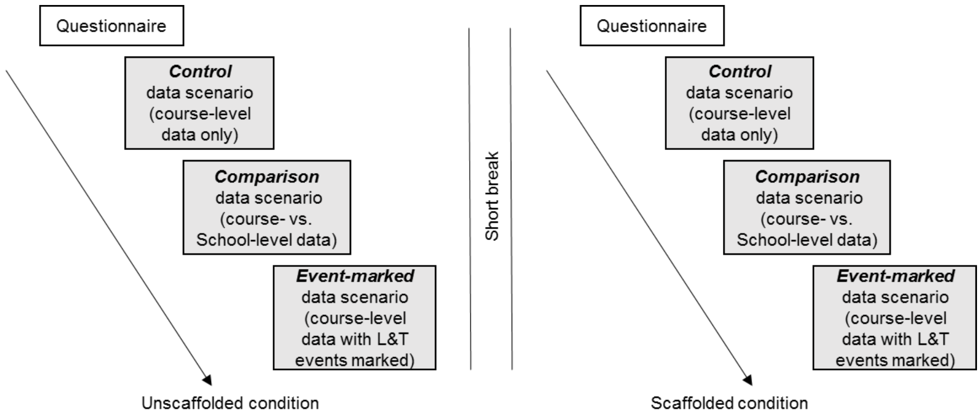

Figure 2. The schematic diagram of the flow of the study. All participants completed the unscaffolded condition first before the scaffolded condition. The order of the data visualisation scenario conditions (dark gray boxes) were counterbalanced across participants.

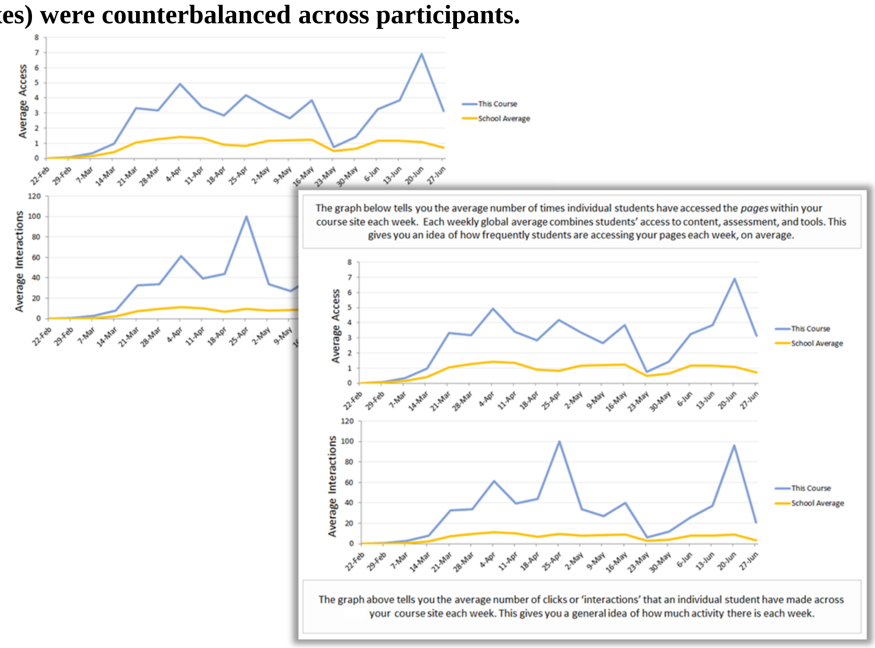

Figure 3. The visual graphical stimuli for the Overperforming group, Compare condition. Background graphs were shown in the unscaffolded condition, foreground depicts that shown in the scaffolded condition.

Procedure

Part 1 of the online questionnaire (Unscaffolded condition) contained several questions about the learning and teaching practices of the academics, a data literacy scale, and followed by the data scenarios. Participants were encouraged to keep their time on each page (one data scenario per page) to under five minutes so as to mimic the face-valid situation of assessing data during the semester. Participants were told to imagine the data they were about to see were from the course with the self-specified course. For each data scenario, participants were asked five open-ended questions designed to progressively tap into deeper levels of inquiry for interpretation, action, and justification for the action. For interpretation and action, participants were asked a general level question (designed to elicit System 1 thinking), followed by a deeper level question (designed to elicit System 2 thinking). Participants had a short break before proceeding to Part 2 (Scaffolded condition). Part 2 was a shorter version of Part 1, comprising the data literacy scale, as well as the set of three data scenarios. In Part 2 however, the visualisations were accompanied by scaffolding text which included a semantic explanation of how the measures were derived. In this paper, I will only be focusing on the qualitative responses to the data scenario questions.

Results

The present research sought to investigate the extent to which visualisation factors affect attentional focus and interpretation of learning analytics, and to better understand schemas and attributions academics make when interpreting learning analytics for enhancement of learning and teaching (L & T) in a setting designed to be close to a naturalistic ‘busy academic’ scenario. The question addressed here is whether the visualisation features differentially shape the interpretive lens with which academics adopt when processing these graphs. To this end, emergent thematic analysis (Massey, 2011) was conducted to assess whether patterns in the responses were systematically similar or different across the three visualisation conditions.

Table 1. Interpretation responses to the question "What overall impression of this course do you get by looking at the data?" coded into surface and deep levels of interpretations categories across visualisation conditions, with example statements of respective categories.

Visualisation condition	Number of Surface Interpretations	Number of Deep Interpretations	Example statement (Surface)	Example statement (Deep)
Control	5	17	"It varies over time."	"A spike on 25th April, low use and interaction on 23rd May and a spike on 20th June. I think in this course, if they are accessing the course then they are also interacting in some way, except that the 25th April"
Comparison	9	14	"My course is doing really well compared to the school average"	"Depending on what is usually offered at the school level, this course seems to do very well… There are specific design elements that encourage interaction on 25th April, but apart from that, the pattern of access generally follows the pattern of interactions."
Event-Marked	4	19	"Student's access increase around the final exam"	"The relationship between access and interaction is not clear. However, I note increased activity at the time of assessment, e.g. Quiz 1 and exam. With quiz 1 interactions increased as access decreased."

As an overview thematic assessment, the responses for the (System 1) interpretation question "What overall impressions of this course do you get by looking at the data?" was coded for categorisation into whether the response was a surface (i.e., general description of pattern observed) or deep (i.e., goes beyond simple description of overall pattern). As can be seen in Table 1, while the distributions of the number of surface and deep interpretations do not significantly differ, X^2 (2, N = 23) = 3.03, p = .22, inspection of the semantics content of the responses appear to vary in systematic ways.

Further inspection of the responses to the questions reveal dominant themes and schemas adopted when interpreting the graphs. Here, I will reveal the emergent thematic patterns according to the revised learning analytics cycle as per Figure 1: analysis – action – consequential thinking, for each visualisation condition.

Unscaffolded: Control condition

Analysis.
Predominately, participants' responses focused on identifying general patterns and trends of activity within the course across the semester. Deeper levels of interpretation include noting of inconsistent activity such as notable peaks and troughs across the weeks, followed by some hypothesizing about potential related learning events. For example, one respondent stated that "(students were) Slow in using the course information and peaks in interaction around the end of April and June. Access and interaction increase rapidly at the end of semester suggests that they are looking for information to prepare for the exam or assessment". When asked "*What notable aspects of the data do you think are important?*", some respondents delved deeper into the analysis aspect of the data (e.g., "Students are not engaged before Week 1, and engagement does not really start until about Week 6. Engagement also drops off markedly at the end of teaching weeks until the end of exam period."). As with the first level interpretation, deeper level interpretation also included hypothesizing about potential related learning and teaching events in the course. On the other hand, some respondents delved deeper into the further inquiry before hypothesizing – this involved asking more clarification questions about the data presented (e.g., "Most importantly, what do the words access and interactions mean. Peaks and troughs and their timing are important as well as actual numbers (on the vertical axis)."), or suggesting other sources of information that would improve their capacity to interpret the data appropriately (e.g., "I need to refer to the course schedule to align the chart with course events.").

Action.
When subsequently asked "*What actions might you take towards enhancing learning and teaching in this course?*" a cluster of responses were focused on increasing engagement earlier (e.g., "Increase engagement at the commencement of the course; create expectation/requirement of consistently accessing and interacting with course material e.g., regular assessments/tasks."). Others stated the need for more information before suggesting any actions (e.g., "Not enough data here or context or detail to make these calls.").

Consistent with the themes above, when asked to provide justification for the proposed action (question: "*Why do you think that might be a good thing to do?*"), three clear themes emerged in the responses. Some justifications were solely based on the data, and were *(1)atheoretical* (e.g., "You may be able to improve the learning in the course by engaging the student from the start and throughout the whole semester.", or "Will keep the access going even when students are busy"), some were (loosely*) (2)theoretically based* (e.g., "Keeping the students engaged across the semester will encourage deeper learning approaches.", or "Engage students in good levels of access and interaction form the beginning; decrease likelihood of final cramming etc"), and finally, some *(3) maintained the level of inquiry* or testing assumptions (e.g., "Given the assumption above, it might improve overall learning.").

Consequential thinking.
When asked "*What do you expect might occur as a result of the changes you are proposing?*", most respondents expected more consistent engagement (by way of access and interactions) throughout the semester as a function of the proposed actions, with students engaging with the course earlier than the apparent start of engagement at Week 3 on the graph (e.g., "Fewer peaks in the processes; more consistent engagement with learning throughout the course."). Others went further to speculate change beyond behaviours to that of student satisfaction and learning as an aspirational outcome (e.g., "increased student satisfaction; community of learning through greater interactions and connectedness", or "Improved student learning and understanding would be good but this may not happen.").

Unscaffolded: Event-marked condition

Analysis.
As with the control condition, the analysis involved interpretation based on student activity within the course, but with more hypothesizing on the basis of the learning and teaching events. This resulted in more consistent critical analysis of the data in relation to learning and teaching events within the course (e.g., "Poor engagement with initial lectures/course introduction; increased participation up to Quiz 1; drop off in engagement in May (lack of further quizzes); peak engagement at end final exams"). Here, more respondents made interpretations of the two graphs in conjunction rather than in isolation (e.g., "Access increases gradually over time until the final exam, excluding late May. Interaction is higher when linked to key assessment", or "The relationship between access and interaction is not clear. However, I note increased activity at the time of assessment, e.g. Quiz 1 and exam. With quiz 1 interactions increased as access decreased.").

A drawback of the deeper analysis question here was that some respondents made inferences about students' approaches to learning from mere LMS access and interactions (e.g., "Students involvement in this course, is based on assessment. Students are not sufficiently motivated in this course. They are simply doing what needs to be done in order to complete the course. They are adopting a surface approach to learning."). Students' cramming behaviour was also inferred without clarification of the source of measures as the basis for interpretation ("Both access and interaction are driven by assessment. Last minute cramming to study for the Quiz & Exam."), where the surge of activity may well have been attributable to completing the quiz within the LMS itself rather than the speculated (lack of) attempts to study. Contrary to this, others approached deeper interpretation of the data with more caution – some questioned the assumptions of the data prior to making inferences about students' learning behaviours (e.g., "Assuming that the graphs represent web hits on certain pages, student access the website more often near exams and quizzes. Perhaps an assignment was due at other peak points in the graph."); others stated their capacity and data limitations and caution in inferring learning from the learning analytics graphs (e.g., "I don't know how to account for the contradiction between interaction peak at assessment two and no corresponding peak for access...this seems odd to me - so anomalies between graphs are significant as well.", or "..This data is not rich enough to infer much").

Action.
As with the control condition, respondents suggested increasing engagement sooner, but with more specific learning and teaching strategies. A large proportion of respondents suggested to increase access by way of increasing the number of assessments throughout the semester, rather than having one big exam at the end following one quiz, and to perhaps make these assessments of smaller stakes (e.g., "Increase access and interaction at the very start; increase assessment/quiz activities so occur on a regular basis; decrease importance of final exam - more equitable assessment tasks). Others went further to suggest specific active learning strategies (e.g., "Try and make the classes more interactive, explaining to students why what they are learning is important, make connections with what they already know or will do"), or to initiate deeper inquiry processes to answer the questions that arose from the initial graphs before making inferences for actioning ("Identifying specifically what type of resources students were accessing and what they were doing with them.", or "Focus group with students where I present the data and ask questions around their study habits").

Compared with the control condition, justification themes for the proposed actions were similar, but again, more specific. As an example justification for spreading assessments across the semester based on the inference that students appeared to be driven by assessments, some respondents justified this proposal atheoretically (e.g., "Gives more data for interventions for students not completing the weekly assessment. Engages students in the course continually on a weekly basis."), or with some theoretical basis (e.g., "Encourage students to engage with the material and make connections with the material which means they are more likely to remember it and want to learn more.”), or with further caution of interpreting of current data as insufficient to make inferences (“Better presentation of the data so that will give me a better understanding of the meaning and give me the possibility to make changes to the course/teaching activities if required.”).

Consequential thinking.
As with the control condition, most respondents expected more consistent engagement throughout the semester as a function of their proposed action, though now with greater specificity in relation to assessments (e.g., “More uniform engagement by students”, or “May study early for preparing for the exam and assessment.”).

Unscaffolded: Comparison condition

Analysis.
The responses in this condition largely centered around the School comparison (21 out of 23 responses focused on this, one focused on the course, one was unsure as to how to interpret the graphs). Themes were similar across both the Over- and Under-performer conditions. Thus, the discussion of responses will not be differentiated by condition. Further to the examples given in Table 2, respondents who did interpret the data more deeply approached interpretation with more caution and inquisition, though maintaining the relative comparison to the School average (e.g., “If these courses have approximately the same number of students then obviously students are accessing this course less than the average compared to other courses in the school.”, or “This course seems to have less access and interaction compared to the school average - but there might be a good pedagogical reason for this (course could be very different type of offering to rest of school)”.)

Action.
Interestingly, the themes emerging from proposed actions were not consistently aligned with the interpretations. While some maintained the schema associated with the School comparison (e.g., “Encourage course convenor to discuss L&T approaches with other convenors - try and improve their courses!”, or “Find out what other members of staff in the school are doing to try and increase levels of access and interactions to at least school levels.”), some continued to propose actions irrespective of the School comparison, as that seen in the Control and Event-marked conditions (e.g., “Face to face interactions early on Setting expectations of behaviour early in semester needs to occur”). Others were hesitant to act on the basis of the graphs in question citing insufficient information to propose action or interpret accurately. When asked to provide justification for their proposed actions, consistency of engagement was framed in the context of a School, rather than within a course (e.g., “Brings a common pattern to the school and brings the course to school levels providing students with a more consistent approach”).

Consequential thinking.
Consistent with the Control and Event-marked conditions, the dominant expectation was that the proposed actions would result in more consistent engagement across the semester. In addition, there were responses that highlighted expectations around a more coherent school (“Better response to course and a more coherent school based approach”), or made references to expected course and teaching evaluations when given relative School average data that places their course to be higher than the average (“My course gets better... and given the lack of interaction with other courses in the school, my SETs and SECs (*teaching and course evaluations*) will shine brightly.”).

Scaffolded condition

To answer the additive question of whether scaffolding improved the information processing of the visualisations, we assessed the responses for any insight clarifications emerging in the responses post scaffolding. Responses appeared to be similar thematically and in depth to those in the Unscaffolded condition, but with fewer responses suggesting there is insufficient information to make meaningful interpretation or inferences.

Discussion

The present paper focused on investigating the extent to which visualisation factors affect attentional focus and interpretation of learning analytics. In particular, the aim was to better understand schemas and attributions academics make when interpreting learning analytics for enhancement of learning and teaching in a setting designed to be close to a naturalistic 'busy academic' scenario. In answering the first question of whether the visualisation differences affect the attentional and interpretive lens with which academics adopt when processing these graphs in trying to answer learning and teaching questions, we assessed the responses to the five open-ended questions of inquiry: two interpretation questions, two action questions, and one consequential thinking question, in line with a revised learning analytics data cycle loop (see Figure 1). The interpretation and action questions were designed to elicit System 1 (fast, automatic thinking), followed by System 2 (slow, deliberate thinking) cognitive processes to assess the functional role of cognitive biases in this context.

Emergent thematic analysis of the responses suggest that the design features tested in this study – control, comparative, and event-marked features – do shape the attentional focus and subsequent interpretation of the data. This was most prevalent in the comparative condition whereby most of the respondents' interpretations centred on the Course vs. School average relativity instead of inspecting and interpreting the pattern changes within their own course. This is unsurprising given the evidence of social comparison tendencies once the attentional lens is focused on the comparative features of the visualisation (Corcoran & Mussweiler, 2010). This suggests that the social comparative feature simultaneously enhanced deeper processing of comparative data, and obscured deeper processing of the data pattern changes within their own course.

Interestingly, when asked to propose actions on the basis of the interpretations in the Comparison condition, some respondents who interpreted in terms of School-referencing reverted back to general course-level actions. That is, respondents were equally likely to propose actions that were School-referenced as they were to propose actions without referencing the School (course-only proposed actions). This is despite having made School-average-referenced data interpretations. This inconsistency in the line of thought in interpretation through to action perhaps indicates a potential gap in the bridging of understanding the data to devising rational, evidence-based action, whereby the addition of more complex contextual factors (such as the additional comparison to School average data) made this more challenging.

Generally, more concrete hypothesizing about student learning occurred in both the Comparative and Event-Marked conditions compared to the Control condition, however focused interpretations and proposals for actions around student engagement and learning were more evident in the Event-Marked condition. Whilst interpretation in the control condition did focus on the course, this was also the condition where academics asked more questions or requested the need for more data before making inferential leaps or proposing actions. Taken together, the findings highlight the importance of aligning design of learning analytics dashboards with the intended educational purpose. Specifically, the factors that impact attentional selection of information for further processing is an important consideration for the future design of learning analytics dashboards, particularly when considering the intended purpose of these dashboards in enhancing learning and teaching whilst minimising errors in inferences from quick glances of dashboard data. Interpretations in the Comparison and Event-marked conditions were consistent with, and largely constrained within the features of these graphs: the comparison line of School average data obscured the course-level pattern variations and highlighted the School-Course comparisons, while the interpretations in the Event-marked condition (graph marked with largely assessment items) revolved around assessments.

The addition of 'deeper dive' (System 2; Kahneman, 2003) questions in this study was intended to elicit deeper inquiry processes in interpretation of learning analytics for devising actions to enhance learning and teaching practice, and in particular, in having greater consideration of the impact of these proposed actions. Here, we observed a consistent emergent theme of academics' expectations of student engagement across the semester shaping their proposed actions. Regardless of the visualisation conditions, academics largely expected students to maintain a consistent level of engagement with their course (at least in terms of online engagement in this context, irrespective to teaching mode). This finding is interesting, as it suggests an expectation that students should engage consistently across the weeks in the semester, regardless of semester breaks and conflicting demands that change over time. This adds the question of how do these educator expectations influence the interpretation and strategies that they may employ to enhance their course for learning. That is, how does this expectation drive their data-informed practice, and how does it influence the behaviours they would like to facilitate in the students (i.e., distinction between engagement as seen with the analytics presented here, and depth of learning). Given the consistency of this expectation, it is possible that this might be an expression of a heuristic shaped by normative institutional or educational discourse. While this contention cannot be determined from this study, this highlights the importance of deliberate consideration of the institutional and support-services framing and discourse-setting around institutional approaches to digitally-enhanced learning and learning analytics in general.

One of the recurring challenges for learning analytics is the conception and measurement of 'learning' in 'learning analytics'. Given that the learning analytics presented in this study were general 'access and interactions' activities across the entire course, the fact that deeper considerations of learning beyond engagement was less evident in the responses in this study suggests that the level of interpretation was for the most part appropriate. Given the concerns in the sector for inappropriate or overinterpretation of learning analytics, the findings indicate some parsimony in this pattern of interpretation of data suggesting that this may not be a concern for the majority of educators in higher education.

However, a minority of respondents did infer learning approaches from this distal data. This highlights the need for more discussions in the sector about using learning analytics as a key measure in learning and teaching, in particular in inferring learning from learning analytics given its measurement properties, reliability, and validity. While learning analytics in this context can open up possibilities for near real-time interventions in learning and teaching design, the considerations of the translation of learning analytics into appropriate interventions remains a challenge that needs to be addressed. In particular is the challenge in inferring learning as a process rather than outcomes (Lodge & Lewis, 2012), as is the more prevalent practice in higher education.

Interestingly, the scaffolding manipulation resulted in minimal change in interpretation. It may be that while scaffolding is necessary to reduce uncertainty, the current manipulation of scaffolding with the semantic information of how the measures were derived is not sufficient to have the impact of improving interpretation of the visualised learning analytics graphs within a short period. That is, the short given duration (under five minutes) to answer the questions for each data scenario was insufficient for participants to encode, understand, and apply the semantic scaffolding (semantic information about what the graphs indicated/ measured) sufficient for the intended purpose. It might be that educators will require more comprehensive, coherent academic development that links the semantic information of the measures with the learning science and learning design to optimise their capacity to truly enhance their practice with data and evidence.

There are certain contextual factors that may impact on the generalisability of the findings of this study to that of other higher education institutions. First, given the numbers of participants in this study, it is worth noting the exploratory nature of this study. Second, it is important to note here that at the time of the study, the amount of institutional or prior exposure to learning analytics is relatively low. Future research could investigate the impact of the design features with academics who may have had more experience with learning analytics to assess the effect on more mature users.

There are a few implications for professional learning. Given that this study was conducted in a university that does not yet have an institutional learning analytics dashboard implemented, this speaks to the level of maturity in understanding use of learning analytics at a deeper level. Indeed, when asked for the types of data they use to enhance learning and teaching, only seven out of 23 participants indicated some experience with using analytics (i.e., Blackboard native performance reports, Yammer, Echo 360). The question remains as to whether this signals the requirement for deeper levels of scaffolding beyond the semantic information of the measures. Future professional learning initiatives and research could move beyond just semantic scaffolding (the "*What")*, but perhaps including inquiry triggering scaffolding using the connectivity principle (e.g., exploring common lines of questioning) and links to relevant literature (i.e., to help with meaning-making and considerations of theory and relevant variables to focus on when using learning analytics). Further, design and training development could consider the general themes that emerged in the justifications of actions in this study – actions proposed were either atheoretically developed, loosely linked to theory, or in some cases, resulted in deeper inquiry process, rather than prescriptive actions. By and large, the main message for educators in general is to perhaps slow down, and make deliberate the cognitive processes involved in interpretation of learning analytics to mitigate some of these automatic processes.

The main rationale for addressing these questions was to better understand the attentional and cognitive processing strategies activated when using learning analytics data for learning and teaching so as to inform more evidence-based designs of future learning analytics dashboards. The preliminary findings in this study suggest that the design features of learning analytics dashboards, such as marking learning events, or overlaying the School average data over the course data, do systematically shape the interpretive lens academics take when using learning analytics to inform learning and teaching. This finding highlights the importance of considering the attentional and cognitive factors when designing the tools, professional learning, and institutional strategies as part of the implementation of learning analytics. I suggest that none of the visualisation examples used here were better than others, but rather that it is important to consider the alignment of the intended purpose and design features of learning analytics dashboards and to be cognisant of the factors that *bias* towards, or as importantly, *obscure* attentional selection of certain features of the data. Further, while cognitive biases may be difficult to mitigate or change, it is worth considering and understanding these cognitive processes in using learning analytics for learning and teaching. While biases may be activated, it may be possible that they can be mitigated when deeper, deliberate consequential thinking processes are engaged in. This is particularly critical when learning analytics is used in conjunction with student demographic data (i.e., labelling bias, stereotypes, etc.; for example, see Ohan, Visser, Strain, & Allen, 2011).

The complexity of interpreting learning analytics for specific purposes in learning and teaching enhancements is clear. While course educators are best positioned to make sense of the data that arise out of their own course context, and apply it to design relevant, effective actions, careful design of the learning analytics dashboards aligned with purposes need to be considered to optimise this capacity. This work could help educators not only develop their teaching practice, but also leverage previously untapped sources of data and evidence in the scholarship of learning and teaching.

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