
HOW DO WE KNOW THEY ARE LEARNING? STUDENT DATA AND THE SYNERGIES OF HUMAN AND ARTIFICIAL INTELLIGENCE (AI)

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Abstract

Artificial intelligence (AI) and the fourth industrial revolution have rapidly become the latest buzzwords in the education industry. Learning analytics and student data have become a central focal point in understanding and evaluating students in an attempt to improve upon the learning environment and experience. This paper explores the history and application of AI and learning analytics in higher education, and then discusses the role of AI in designing, delivering, and evaluating the online learning experience. The research presented shares the experience of an instructional team for two cohorts of an online graduate course and the team's use of available data and learning analytics in delivering the course. Based on the literature and the instructional team's experience, the paper then proposes a framework for the use of AI in online teaching and learning (OTL).

Introduction

Traditionally, education has always measured student learning in various forms, from inter alia assignments and observations to examinations and/or practical work. Much of the student data collected has been proxies on which educators and institutions have made evaluations to determine whether students have mastered a particular subject, skill, and/or competency. As higher education institutions increasingly move online and learning and teaching becomes digitised and datafield, a greater variety and granularity of student data, from more sources and often in real-time, is available to institutions, educators and support staff than ever before. Subsequently, there has been increased attention to student data and a proliferation of strategies to harvest student data – from scraping facial expressions, to multimodal data and social network analysis. As more data becomes available, its amount and complexity exceed the human capability to effectively process and analyse that data. In addition, the data revolution is accompanied and also perpetuated by increased hardware and software capacity, tools, and the commercialisation of data. However, in the

final analysis the question remains: how do we know students are learning? What data do educators and support staff have access to, under what conditions and how are they using the data to help students engage more, and hopefully, learn more effectively? This paper explores the use of learning analytics and AI in online teaching and learning through a review of the literature and collaborative ethnography, and then proposes a synergistic framework that uses artificial intelligence (AI) + learning analytics + pedagogical/support interventions for improving both the learning (students) and teaching (instructor) experience and environment.

Learning Analytics and Facilitation of Learning

At the first Learning Analytics and Knowledge conference (LAK'11) in Banff, Canada (<https://tekri.athabasca.ca/analytics/>), an initial definition of learning analytics was introduced by conference organisers, describing learning analytics as: "...the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs" (Siemens & Long, 2011; p.34). While there are other definitions of learning analytics, for the purposes of this paper, we will use this definition, particularly due to its emphasis on pedagogy in considering the implications of learning analytics. A large section of research on learning analytics focuses on its *potential* to impact positively on student success and retention, and although some evidence paints an imperfect picture (Ferguson & Clow, 2017; Kitto, Shum, & Gibson, 2018), and there is ample evidence that, depending on a number of variables, learning analytics *do* impact positively on student success and retention (Lim et al., 2019; Pardo, Jovanovic, Dawson, Gašević, & Mirriahi, 2019; Wong & Li, 2019).

However, learning analytics still face several challenges in the broader context of higher education. For example, Klein, Lester, Rangwala, and Johri (2019) map learning analytics at the intersections of institutional commitment and individual action, and Lim et al. (2019) question the value contribution of learning analytics and ask "what changes and for whom?" Aligned to this question is the exploration by Slade, Prinsloo, and Khalil (2019) in mapping learning analytics at the intersections of student trust, disclosure and benefit. As learning analytics mature, researchers acknowledge that learning analytics is, in many ways, still imperfect (Kitto, Shum, & Gibson, 2018), but, there is also a commitment to increase the positive impact of learning analytics (Dawson, Joksimovic, Poquet, & Siemens, 2019). In the context of this paper we accept that learning analytics is used by educators and students on the course level (Long & Siemens, 2011) to provide (personalised) feedback to students on their progression (Gašević, Dawson, & Siemens, 2015) and feedback to faculty and support staff regarding excessive workloads or the unequal spread of tasks over a specific tuition period (Rienties, Cross, Marsh, & Ullmann, 2017). While a significant part

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of learning analytics is on identifying students-at-risk and to inform appropriate interventions, in this paper we point to the potential of learning analytics and the use of AI to increase the appropriateness and effectiveness of teaching for all students, and not just at-risk student – formative interventions from data during the course and summative intervention in design after a course. In light of the variety, volume, granularity, and velocity of student data available in online learning environments, it is increasingly challenging, if not impossible for humans, without some form of algorithmic decision-making system, to make sense of the data, analyse it for trends, and to provide timely feedback to students and inform pedagogical and support interventions. In this collaborative ethnography, we will share experiences and evidence that even in relatively small online classes, some form of algorithmic decision-making system will greatly free educator time, but also increase the effectiveness and appropriateness of teaching and support. Despite, and amid the ethical concerns pertaining to algorithmic decision-making systems, we have to consider the potential of learning analytics to inform pedagogy in ways previously impossible. In the next section we will attempt to define AI in the specific context of online teaching and learning (OTL), after which we will share a brief introduction to our methodology, the findings of our collaborative ethnography and concluding this paper with a number of pointers.

Towards a Definition of AI for Online Teaching and Learning (OTL)

Before offering a practical working definition for AI in OTL, it is worth reviewing how AI has typically been interpreted. In general, the AI construct has been dominated by the idea that computers and/or technology will *replace* functions and tasks typically done by human beings (Newton & Newton, 2020; Selwyn, 2019). It is then a reasonable assumption that AI in education is synonymous with replacing the role of the teacher. In response to this view, AI in OTL can be based upon the following assumptions: (a) AI in concert with design-based data sets enhances and strengthens rather than diminishes the teacher's role; (b) online technical design, course design, and support systems are directly linked to the data sets related to quality teaching and enhanced student learning, and (c) the most important impact of AI in OTL is leveraging data sets linked to student engagement and performance and subsequent learning analytics by teachers and support staff. These tenants suggest that AI in OTL is directly linked to providing data sets supported by scholarly research and practice not only for improving student learning but enhancing teaching. Drawing upon these tenants and OTL research, we offer the following definition of AI in OTL:

“Artificial intelligence (AI) in online teaching and learning (OTL) is defined as the combination of assumptions about data sets, technical design, learning design, and support systems and the strategies used for gathering and evaluating data sets aligned with quality teaching and learning and based in teacher presence, student engagement and interaction, student cognitive and social presence, and assessment of performance.”

From this definition emerges the use of AI to create systematic learning analytics that lead to tactical interventions by online teachers/designers, thereby improving and validating not only pedagogical design and student support, but also student learning. From a practical standpoint, innovative design and support features would cover data gathering activities that were previously done manually. This is not replacing the teacher through automation; in fact, it is creating more time for the instructor to analyse data sets and make formative changes to instructional design and delivery as appropriate.

Algorithmic Decision-Making as a Pedagogical Tool

We propose pedagogy as the deliberate and strategic structuring of teaching and learning activities, resources, and sequencing to facilitate and evaluate learning (Prinsloo, 2016). Underpinning this notion of pedagogy are four activities: noticing or sensing student behaviour and engagement, processing the information, adapting the pedagogical approach based on group or individual behaviour or performance, and continuously monitoring the impact of the change in pedagogical strategy or adding activities or resources on student learning. These activities resemble Danaher’s (2015) four essential components in human decision-making: *sensing* (the collection of data from one or a variety of sources); *processing* (organising collected data into useful chunks/patterns as related to categories, goals or foreseen actions); *acting* (using the processing outcome to implement a particular course of action); and *learning* (flowing from the previous three actions, the system learns from previous collections/analyses and adapts accordingly). For example, within the online classroom, the educator may notice that a particular student is not engaging, e.g., has not submitted an assignment or responded to a question. The educator then *processes* the information (classifying the student as at-risk of failing and/or in need of follow-up), *acts* (sending the student a query pertaining to the non-submission), and *learns* (making sense of whether the query changes the student’s behaviour). As level of difficulty increases with the number and intensity of activities, structured engagements, and readings, educators may struggle to notice certain behaviours and to respond timeously to students at risk of disengagement and/or failure, thus justifying the use of learning analytics (Prinsloo, 2017).

Brief Notes on our Methodological Design and Norms

Collaborative ethnography entails the basic and accepted principles of traditional ethnography, but acknowledges the reiterative processes between researcher and/researchers and their research communities to collect, make sense, and understand data. For example, May and Pattillo-McCoy (2000) describe collaborative ethnography as “useful for providing a richer description, highlighting perceptual inconsistencies, and recognising the influence of ethnographers’ personal and intellectual backgrounds on the collection and recording of data” (p.65). Seminal collaborative ethnography is the recognition of the subjectivity of experiencing the same phenomenon, and the fact that sensemaking of reality in a particular collaborative research context is “ultimately unstable and personal” (May & Pattillo-McCoy, 2000; p.66). This raises a particular obligation of researchers doing ethnography to interrogate our narratives and the writings co-produced and collected (Fine & Weis, 1996). Seminal to collaborative ethnography is researching “the *same social phenomenon*... but from *different social settings*” (May & Pattillo-McCoy, 2000; p.66). Collaborative ethnography focuses on the biographical and context-specific factors of each collaborating researcher as a key element in the collection, analysis and interpretation of data (Belgrave & Smith, 1995). Core to this collaborative ethnography is that it was in its core *accidental*, described as “the systematic analysis of prior fieldwork. It utilizes extant data ‘accidentally’ gathered ... to provide insight into a phenomenon, culture, or way of life” (Levitan, Carr-Chellman, & Carr-Chellman, 2017; p.1). Accidental collaborative ethnography describes the reflective process when “practitioners often discover important phenomena that could contribute to research knowledge and organizational improvement, if explored rigorously, reflectively, and practically” (Levitan, Carr-Chellman, & Carr-Chellman, 2017; p.3). Collaborative ethnography not only makes room for different interpretations of and knowledge influencing the interpretation of a particular phenomenon, but also acknowledges “asymmetries among persons working together which shape their joint endeavors” and how the interpretation is entangled in emotion that “deepens the challenge of working together and trying to share knowledge and negotiate power relation (McCabe, & Cultural Connections, 2014; p.13). For a full discussion of collaborative, accidental ethnography also see e.g. Fuji (2015), Lassiter (2005) and Poulos (2009).

Trustworthiness and Ethics in Collaborative, Accidental Research

As already stated, collaborative ethnography foregrounds context-specific factors as well as unique biographical details and experiences of collaborating researchers as key elements in the collection, analysis and interpretation of data (Belgrave & Smith, 1995). The beauty of this is that differences in interpretation of data are not only appreciated but also *foregrounded*. Instead of differences being seen as eroding the trustworthiness of the

analysis, the transparency regarding the differences confirms the trustworthiness. Core to the notion of trustworthiness in collaborative research is the notion of trust – “When people come to trust each other in collaborative settings, a favourable milieu for validating sources of knowledge brought by other team members comes into existence” (McCabe, & Cultural Connections, 2014; p.14). Core to collaborative ethnography is that researchers should “situate themselves in the study by revealing their background and personal perspectives, theoretical stance, style of interaction, political aims, and understandings acquired through the research via ongoing journaling, with participants in dialogue, and in the research write-up” (Lapadat, 2017; p.591). The researchers (one female, and two males) were from different geopolitical contexts (Germany, Romania and South Africa), all with extensive experience in various aspects of OTL ranging from teaching and leadership, management and research. With regard to the ethical issues in collaborative (auto)ethnography, Lapadat (2017) writes that it “adds a multidisciplinary lens to inquiry, thereby reducing the likelihood of criticisms about lack of rigor, narcissism, or self-indulgence” (p.599). Except for realising the potential of multiple perspectives, collaborative ethnography also “provides a structure to support witnessing” and “flattens power dynamics in the team because all the coresearchers are vulnerable in sharing their stories” (Lapadat, 2017; p.599).

Research Context and Data Sources

The authors were all part of an online course in a postgraduate programme at a German public university. The 15week course was an introductory course covering the broad scope of established principles, theories and practices in the use of technology in OTL. All students were practicing faculty and administrators from one university outside of Europe. The first cohort consisted of 10 students (Case 1) taught by one primary instructor assisted by a mentor, and the second of 12 students (Case 2) co-taught by the primary instructor from the previous semester and another instructor, assisted by a mentor. Instructors delivered instruction through highly structured online discussion forums and providing formative feedback on 13 learning activities, which were then incorporated into a final portfolio used as the primary assessment. Automated learning analytics included when and how often students logged into the course, and number of student posts; all other data was manually extracted from the course. In his work of sources of data, Kitchin (2013) refers to three sources - directed, automated and volunteered and all these three sources were available to instructors. Data collected from and provided by students at the point of registration equals directed data as source while the students volunteered data in the profiles and shared written introductions and short introductory videos of themselves. Student posts and responses in the discussion forums also provided some understanding of their engagement with the materials, applications to their respective contexts and

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sharing opinions and insights regarding fellow students' posts. Only the instructors also had access to basic login data consisting of the date and times of student logins which resembles the 'automated' data category. From these data sources instructors could make sense of how students were progressing through the course, the depth of their understanding and, to some extent, the depth of their engagement in the course.

While the same instructional design was used in both cohorts, and the two cohorts both consisting of students of the same institution and context, the first cohort (Case 1) was, from the start actively engaged and almost hyperactive (222 posts) resulting in the instructional team sharing notes of how difficult it was to keep up with the group. During the same period, the instructors posted 234 posts broadly categorised as teaching, social and cognitive presence. The learning and behavioural data (e.g. online engagement, quality and frequency of the posts) provided the instructional team with enough data to assess students' progress and the effectiveness of the pedagogical structure and strategy. The second cohort (Case 2) presented a very different scenario. Some students in the group only started posting introductions in the second week of the 12 week course, and the instructors sent supportive reminders via email, encouraging engagement and offering support. Data available made it difficult for the instructional to assess student progress and whether students were in fact learning. Of the cohort of 12 students in the second case, two students contributed almost half (98) of the total number of posts (209). Posts from the instructional team numbered 218. Despite numerous instructional interventions, nothing seemed to make a difference to the level and quality of engagement in Case 2. Student login data confirmed the lack of engagement by the majority of students. Data used in this collaborative ethnography included archived email communication of and between instructors, archived login data, memories and collaborative storytelling, shared reflections and recalling as "a way of bringing out memories about critical events, people, place, behaviours, talks, thoughts, perspectives, opinions and emotions" (Chang, 2013; p.113). Looking at this data retrospectively, the researchers reflected individually and collaboratively on the potential to AI in OTL. We shared these reflections in emails and in the various drafts of this paper.

Emerging Analysis and Findings

Throughout the two cases, the instructional team communicated via Skype, group and individual emails, and telephone calls. Notes from these meetings, calls, and emails spanning the time period covering both cases formed the basis for this emerging collaborative ethnography. The purpose of this paper is *not* to present the full analysis of these collected data and collaborative, accidental sense-making, but to use background,

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context and data as the basis for presenting a framework for AI in OTL. Main themes that emerged from the analysis are shown in Table 1.

Table 1: Main themes in collaborative ethnographical analysis

Instructional Team	
Case 1	Case 2
Theme: Making use/sense of login data "Most students have logged in at least once and it is looking good" (Instructor A email end of the first week) "The login data really assisted me to compile the mid-semester report" (Instructor B email, 5th week) Theme: Making use/sense of discussion post data: "Have you seen the latest response by Sandra (pseudonym)? She has really keeps going and are responding to all the other students' posts, often more than once" (Instructor B email, end of week 4) Theme: Instructor experience "Ugh. I just cannot keep up with this group – this is intense!" (Instructor B email end of the second week) "This counts most probably as once of the most rewarding but also exhausting experiences I've had in teaching online. It was like teaching one-on-one for every day for 12 weeks!" (Instructor B email, end of week 9)	Theme: Making use/sense of login data "I checked the login data and some students have not yet logged in once" (Instructor A email end of the first week) "Nothing is happening. They are simply not even checking in" (Instructor A email end of the third week) "Give them time. Though I share your concerns, let us not get impatient. I am sure they will rise to the occasion" (Instructor B to Instructor A end of the third week) "Dear ... according to our view of your login data, we see that you have not logged in for the last 7 days. Is there anything we can assist you with?" (Instructor A email to student) Theme: Making use/sense of discussion post data: "What is happening? Where are the students?" (Instructor B email end of the second week) Theme: Instructor experience "What more can we do? I check the login data every morning just to see which students made an attempt and I reach out to them to see if I can help, but there is just nothing. I am starting to despair" (Instructor B email end of the third week) "This is simply the worst experience I've had of teaching online. Nothing we do makes a difference. This is a nightmare" (Instructor B email, end of week 7)

Main Findings from the Login and Response Data

Most students logged in at least once in the Very few students logged in during the pre-week. Even during the week preceding the beginning of the first official week of the course, only two students posted the course. Most students logged on every day, required introductions and introductory videos. By the 4th week and several students responded to several some students still have not posted the introductions and of fellow student post introductory videos. The majority of students logged in only once every third to fourth day, if not once a week. The level (number of posts) and quality of engagement were, in general dismal excluding the sterling work by two students. In follow-up emails and telephone

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calls, students complained about accessing and navigating the site, finding the required readings and uploading the tasks and assignments.

While the two cases analysed can be portrayed as two ends of a spectrum, a very active, engaged classroom on the one end and a very unresponsive class on the other end of the spectrum, the final academic outcome of these two cases were not significantly different. The seeming similarity in the outcomes of these two courses, is, however, not the focus of this paper. It is also not the purpose of the paper to speculate on why students, from the same institutional context, responded so differently to the same learning design, cognitive, social and teacher presence, and assessment strategies. Of interest in the scope of the potential of AI in OTL is the *data* the instructional team had access to, how the data informed their strategies and how AI could have *supported* teaching and learning. In both cases, the instructional team observed and sensed certain behavioural behaviours, processed what the behaviour meant, acted, and learned (see our earlier reference to the work of Danahar, 2015).

Towards a Framework for AI in OTL

In an attempt to bring clarity to the experience, instructors developed a conceptual framework based on the literature and their experiences in understanding the role of learning analytics in adapting and customizing pedagogy to improve the learning environment, Figure 1 presents this conceptual framework, which incorporates components of Garrison, Anderson and Archer's Community of Inquiry (CoI) (2000): teacher, social, and cognitive presence. The outer ring details the design infrastructure necessary for AI (technical-digital systems) to set the parameters for gathering data sets within the next inner ring.

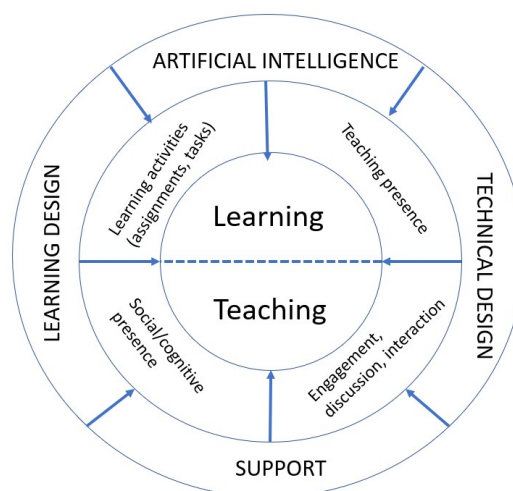


Figure 1. A Framework for AI in OTL

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In the second ring are the key data sets: (a) learning activities (login data, cognitive depth and understanding in participation in discussion forums; assignment data); (b) teacher presence (discussion posts, responses to student posts, emails to individual students); (c) student engagement and discussion (number of original posts and responses; network with fellow peers) and (d) student social and cognitive presence (evidence of reaching out socially or cognitively). The data underpinning these four “inner” elements in the nexus of teaching and learning have been confirmed in research (Garrison, 2016; Rockinson-Szapkiw, Wendt, Whighting, & Nisbet, 2016; Wicks et al., 2015). We propose that these four elements can furthermore be embedded, related to, and interdependent on learning design, student support, technical design and AI. General observations in leveraging these data sets for subsequent learning analytics use and interpretation include:

1. Increased engagement and quality discussion interactions (teacher to student, student to student, student to content, student to self, student to community) can lead to deeper learning and critical thinking amongst students.
2. Performance validates knowledge and understanding, measures learning, is directly related to content knowledge and mastery, and is a valid and reliable measure of learning.
3. Cognitive presence is more than student interaction with content; it is also an extension of Piaget’s (1932) constructivist theory of Cognitive Adaptation where students can assimilate and/or accommodate new knowledge into existing cognitive schemes (knowledge banks) and apply that knowledge to practical realworld situations and scenarios.
4. Student social presence in the online classroom is a general indicator of engagement, knowledge, and learning, with learners constructing their realities and learning from social relationships and interactions; students’ social engagement may be linked to greater motivation and psychological comfort in the online classroom, making them feel a part of the group, course, and institution.

Central to realising the potential of learning analytics is the collection, analysis, measurement and analysis of student data. But as we have stated, the complexity of data, as well as the amount of data especially in large classes, may make human sensing, processing, acting and learning increasingly impossible. Danaher (2015) notes a possible solution by mapping the intersections between human and algorithmic decision-making by pointing to the many (256) different possibilities considering when humans are on their own, or humans are together with AI, or AI with humans who supervise, or AI who independently engage with data – sensing, processing, acting and learning. For example, an algorithm can sense that a student has not logged in for a week and alert the instructor

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who will make sense of the data, and act by sending an email. Or, the algorithm can sense, process, and act on its own, and only alert the human educator if there is no behaviour change. The two cases discussed above visa-vie AI and selected for learning analytics are consistent with the basic purpose of this paper – AI + learning analytics + interventions = improvements of learning (students) and improvements for learning (teachers). Moreover, teachers and designers may opt to target other data sets pertinent to student behaviours and learning which in turn may influence the specific algorithms chosen. The framework above is a conceptual starting point that draws upon data categories that have been supported in previous empirical study and theory.

How do these factors play out within the context of serving as AI data sets in online classrooms? First, engagement and interaction can be easily measured by student presence in the classroom. In reviewing the numbers in the two cases presented, it would seem that students posted about the same (Case 1: 222 posts; Case 2: 209 posts); however, here we must dig deeper to determine the significance of the data. In Case 1, this scenario may have eased some of the instructor responsibility by making sense of login and posting data and alerting the instructors. Though the student cohort was relatively small, the intensity of the course (both intellectually but also in terms of tasks and assignments) and the flurry of activity meant that the instructor could easily have missed the data. AI could also have supplied some insights in cognitive density or network analysis to assist the instructors making informed pedagogic decisions. We suggest that deeper dialogue and application of knowledge (cognitive presence) is a stronger measure of student learning than infrequent posting and short posts supporting another student's strong posts. Students who contribute moral support to other student posts in discussion forums is admirable, but this is not the same as students who post deep, content based, practical posts in discussion posts. Mutual support is important, but this is not deep learning and analysis. The quality and depth of students' discussion posts is a reflection of their cognitive presence. Students who do the readings, reflect upon this content, assimilate it within their existing cognitive structures then move to discussion posts that reflect valid learning particularly if the student can extrapolate the key concepts to real world practical examples and scenarios. In sum, this means as teachers we must analyse the quality and depth of discussion interactions, not just how many.

Thinking through the potential of AI in a *relative data-poor* context like the one presented in the second case (discussed above) is more difficult. Student engagement is weak if the only measure is how many times the student enters the classroom or how long they are in the classroom. It is also crucial to note that the fact that students do not engage does not, necessarily mean that they are in trouble or not learning. Teacher presence is also a factor and can also be easily established based on analytics. However, here again, we must dig

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deeper into the context – and those activities that occur “behind the scenes” (e.g., e-mail interventions). AI can leverage technology to help teachers monitor just what and when students enter the classroom which in turn create data patterns that can validate learning and initiative specific interventions to improve the learner experience; underpinning increasing the potential of AI is, however, the need for students to login. As can be seen from the analysis, the instructors were closely watching the login data to process and act on the information, with no visible impact on student engagement. Data that the instructors did not have access to that may have informed pedagogy and support are, for example, whether students have downloaded the prescribed resources, watched (and finished watching) the prescribed videos, established patterns between login data and moving around on the course site. This data, and use of AI, may have added our understanding of their learning journey. We often assume that if students are not engaging, they are not learning, but as the comparison of the course outcomes suggest, there was no significant difference.

Conclusion

Appropriately and ethically designed AI for OTL can lead to pedagogical interventions in online learning that can produce improvements *in* learning (students) and improvements *for* learning (teachers/designers). Moreover, this synergy of AI and data is consistent with empirical research – data matters – design matters – formative interventions matter – and engagement and interaction in the learning process – matter. Within the proposed definition put forward in this study of AI related to online learning in concert with the framework outlined in Figure 1, refinement of this framework has implications for future research. What is the potential of AI to scale understanding, feedback and support? What ethical considerations and regulatory (GDPR) issues may emerge around online learning? (Prinsloo, 2017) How do the three “Cs” of context-culture-communication enhance or create barriers to the AI-data synergy? Indeed, AI + data + pedagogical interventions may, in fact, create a brave new learning world for online learning students and teachers.

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