Disruptive democratisers? The complexities and incongruities of scale, diversity and personalisation in MOOCs

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Massive open online courses (MOOCs) have been signalled as a disruptive and democratising force in online, distance education. It is claimed that MOOCs have unique characteristics that challenge traditional parameters of learning (and education). These characteristics act as a leveller by offering equal access to Higher Education to billions of learners worldwide, reducing a huge divide between approximately 7% of the world's population who have a degree and 93% who do not (Bloomberg, 2011).

Advocates of MOOCs also promote their ability to provide forms of teaching and learning more relevant to a hyper-connected, digital age and which are more attuned to the needs of people, particularly those wishing to up-skill and engage in life-long learning. As Andre Dua (2013), a Senior Partner at McKinsey & Company, claims:

> What most people—including university leaders—don't yet realize is that this new way of teaching and learning, together with employers' growing frustration with the skills of graduates, is poised to usher in a new credentialing system that may compete with college degrees within a decade. This emerging delivery regime is more than just a distribution mechanism; done right, it promises students faster, more consistent engagement with high-quality content, as well as measurable results. This innovation therefore has the potential to create enormous opportunities for students, employers, and star teachers even as it upends the cost structure and practices of traditional campuses.

Indeed, MOOCs have become an industry in their own right. ClassCentral, a website aggregating data and information on MOOCs, listed 30 MOOC providers in 2017. These providers collaborate with over 800 universities and companies to offer over 9,400 courses, more than 500 MOOC-based credentials, and more than a dozen graduate degrees. 20 million new learners signed up for their first MOOC in 2017, bringing the total number of MOOC learners to 78 million.

The four dimensions comprising the acronym MOOC – massive, open, online, course – simultaneously represent valuable assets that underpin the promise of MOOCs as well as posing challenges for MOOC designers and facilitators and leading to a number of contradictions associated with MOOCs. Massive refers to the scale of the course and alludes to the large number of learners who participate in some MOOCs. It is closely connected to open, which can refer to access; anyone, no matter his or her background, prior experience or current context may enroll in a MOOC as well as to cost – that a MOOC is available free of charge. New technological infrastructure and digital technologies are not only providing wide-scale access, but also enabling new approaches to learning and the repositioning – if not in practice then theoretically – of learners, educators and institutions. As Selwyn observes: 'the ever-expanding connectivity of digital technology is recasting social arrangements and relations in a more open, democratic, and ultimately empowering manner.' (Selwyn, 2012, p2).

However, the current reality of learning in MOOCs remains distant from this alluring promise. There continues to be considerable variation both in the nature of learning that MOOCs offer and the ways in which individuals choose to engage with them. As the authors have previously noted:

> The specific nature and composition of individual MOOCs are profoundly shaped and ultimately the product of their designers and instructors, the platform and platform provider, and the participants, all of whom bring their own frames of reference and contextual frameworks. (Hood & Littlejohn, 2016, p. 5).

Successful and effective large-scale online education is expensive and notoriously challenging to produce and deliver (Ferguson & Sharples, 2014, 98). Furthermore, the number and potential diversity of learners, in terms of background, geographic, motivation, previous experience and ability to learn, pose substantial challenges for MOOC designers and facilitators. The corollary is that the outcomes of a particular learning experience will differ considerably depending on the student and his or her ability to learn, leading to what Selwyn (2016, p.31) describes as 'inequalities of participation'.

One of the most visible examples of this sort of inequality is that, although MOOCs are opening up access to education, they tend to attract people who have already experienced university education (Liyanagunawardena et al, 2015). This inequality is heightened by a general design issue in that, rather than offering scaffolds that support people who are not able to act as autonomous learners, MOOCs often are designed to be used by people who are already able to learn. Another design barrier is that MOOCs often mimic traditional education systems by requiring learners to conform to pre-defined learning objectives, rather than freeing learners to chart their own paths. These norms sustain the traditional hierarchy within which the novice learner is subjugate to the expert teacher. A particularly troubling feature of MOOCs is that this power structure is not always visible, since it is embedded partly within the algorithms and analytics systems that underpin MOOC tools and platforms. These features of MOOCs may cause an unintended divide that disadvantages learners who do not have the confidence or ability to learn in MOOCs.

This chapter explores these incongruities. Taking the learner's perspective, the chapter discusses how learners participate within and self-regulate their learning in a MOOC. The chapter argues that variations in behavioural participation patterns are to be expected where large numbers of learners engage in learning with diverse motivations. This brings into question forms of support primarily based on and in response to learner behaviours and actions. Analytics-based tools and systems being used to support learners tend to analyse what learners do within a MOOC and correlate factors associated with this behaviour with factors that are associated with successful completion in MOOCs. Yet, not every MOOC learner will intend to complete the course. Some may 'drop in' to learn a specific concept, then 'drop out' without intending to complete an assessment (Milligan, Littlejohn & Margaryan, 2013). Predictive analytics tools that predict outcomes relative to pre-desfined course objectives, without checking whether the learner intends to follow these outcomes, do not serve the needs of the student or align with claims that MOOCs are a democratizing form of learning.   To fulfill this goal, MOOC platforms need to be underpinned data analytics designed to scaffold MOOC learners in ways that allow them to be able to identify and achieve their own learning goals on their own terms, rather than following a course pathway. The ability to self-regulate learning is a critical competency for learners to be able to engage fully in open, online lifelong learning.

Individualism versus idealism; the position of the learner in MOOCs
The individual is positioned as the locus of determination and control in a MOOC, where learners are able to set their own terms of participation. This idea differentiates MOOCs from much of 'traditional' education, where course objectives and learning designs are pre-defined by the teacher. Compared with university students, MOOC learners have a very different relationship to teachers, course requirements, learning processes, and even the institution offering the MOOC. The open, flexible nature of MOOCs in theory - though not always in practice - enables individuals to determine with what, how, when and for what ends they will engage. The open learning structure of a MOOC, coupled with the diverse backgrounds of the participants, results in MOOC learners typically having a wider range of motivations and needs for learning than is normally observed in a conventional course. The flexible structure of MOOCs, in which there are few barriers to entry and minimal formal consequences for learners who choose to 'drop in' and 'drop out' of a MOOC, leads to fluidity in learners' behaviours and actions. (Yang, Sinha, Adamson, & Rose 2013).

However, this apparent openness and flexibility in MOOC participation does not always lead to the intended promising outcomes for learners. MOOC designers tend to focus on 'equality of access' to a course, but seldom address the equally important need to ensure learners experience 'equality of participation'. As Selwyn (2016) explains:

> The assumption that all individuals can navigate their own pathways through digital education opportunities implies a corresponding withdrawal of expert direction, guidance and support. While offering an alternative to the perceived paternalism of organised education provision, this approach does bump up against the widely held belief in education that learning is a social endeavour that is best supported by more knowledgeable others. (p.74)

Furthermore, while MOOCs emphasise the primacy of the learner and the role individual learners' play in structuring their engagement, there has been a tendency in the literature on MOOCs to focus on 'design solutions' that encourage desired modes of engagement and participation (see for example Guàrdia, et al, 2013; Daradoumis, et al, 2013). Cottom (2014) argues that online systems get designed and configured to 'the norm' of a self-motivated, highly able individual who is 'disembodied from place, culture, history, markets and inequality regimes'. That is, MOOCs are designed for those who have the social and educational capital to engage with the learning opportunities presented. These MOOC designs typically disregard the offline context of the learner and how this might influence and shape both the nature of their engagement and the outcomes they desire from their participation.

Researchers exploring the nature of learning and engagement of learners in MOOCs, while recognising that MOOCs represent something qualitatively different from traditional forms of education, have continued to default to traditional metrics of learning – associated with retention, progression and completion rates – as the dependent variables in their analyses. That is, learners in MOOCs continue to be judged according to conventional measures of learning, such as passing tests and assignments and becoming accredited. However, the authors' own research into learning behaviours in MOOCs, which includes several qualitative analyses of narrative accounts of MOOC learners in their own words, has identified four distinct ways of 'being a MOOC learner' (Littlejohn, Hood, Milligan & Mustain, 2016) . Not all these 'ways of being' align with the approaches to learning students adopt on conventional courses.

Four ways of being a MOOC learner
We analysed narrative accounts of MOOC participants where they described their experiences of being a MOOC learner (Littlejohn & Hood, 2018). This analysis allowed us to interpret and illustrate forms of learning engagement, by establishing four distinct ways learners approach learning in MOOCs, described below (Figure 1). There are already a number of typologies of MOOC learners that focus solely on how learners behave in a MOOC platform (see for example Bachelet & Chaker, 2017; Milligan, Littlejohn & Margaryan, 2013; Tschofen & Mackness, 2012).
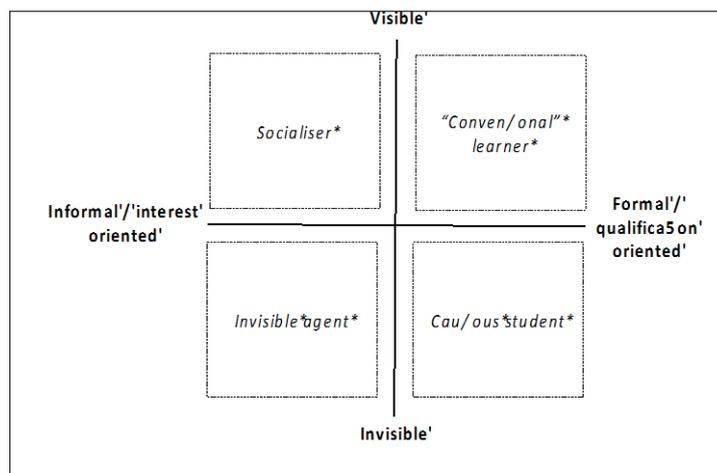

Figure 1: Ways of being a MOOC learner

The four ways of acting as a MOOC learner include being:

Visible: The extent to which a learner actively participates online and is known to other participants.
Invisible: The extent to which a learner engages passively, without actively contributing or becoming known to others
Formal/qualification oriented: The extent to which a learner is concerned with completing a course and engages in the MOOC like a traditional learning activity
Informal / interest oriented: The extent to which a learner is motivated by self-interest rather than external reward and is less structured in their engagement.

This framework differs from previous typologies in that it focuses on ways of being a MOOC learner and there is no attempt to suggest that a learner will always conform to a single way of 'being'. Indeed, it is very possible that an individual learner will move along both axes, from visible to invisible and from formal/qualifications oriented to informal/interest oriented when engaged in different MOOCs or sometimes within a single MOOC. In creating this framework, the authors are not trying to suggest that any single 'way of being' is more or less effective than another. It depends on the learner's own goals, motivations and context.

These four distinct ways of learning are described below. None of these approaches to learning is more or less effective than another. Similarly, there is no attempt to suggest that a learner will always conform to a single approach. Indeed, it is very possible that an individual learner will move along both axes, from visible to invisible and from formal/qualifications oriented to informal/interest oriented when engaged in different MOOCs or sometimes within a single MOOC.

These four learner "types" are illustrated through narrative portraits of each type. These narratives are drawn from the stories of actual learners who participated in the Introduction to Data Science MOOC in 2014. The MOOC was created and facilitated by the University of Washington and hosted on the Coursera platform. These narratives are part of a larger study examining the self-regulated learning of 788 participants in the MOOC.

The 'conventional' learner is one who is motivated to complete the course and gain certification. These learners are sometimes referred to as 'ideal learners' because their behaviour fits with what MOOC designers and facilitators believe to be optimal for course completion (even though this behaviour may not fit with the learners' own objectives). They tend to follow a largely linear trajectory, engaging with the majority of the content and completing the activities and assessments. Furthermore, they are active contributors to the discussion forums, both asking and answering questions, and consider collaboration with other participants a key part of the MOOC experience.

I was aiming to get a certificate of completion and to get a passing distinction grade out of the class. I took the course very seriously from the beginning and this meant that I planned to watch all the videos and go through all the assignments. I have at least completed all the compulsory assignments. I can tackle courses very efficiently when I'm doing them as a student. First of all I watch lectures and after that I try to answer all the quizzes and questions, and after that I go to programme assignments

I think that the forums are very important because all the classmates could have the same problems that I have and I think the forums are very important for all the courses. When I'm working on a quiz or an assessment I like to go into the discussion forums. And it's the collaboration around the assessments that I will get involved with on the forums.

The cautious student also has a goal to complete the course and as a result - similarly to the 'conventional' student - will engage with the majority of the course content and activities. However, they often are not as confident and at times struggle to regulate their learning and to select the best learning approaches for their needs. Furthermore, they typically are reticent to post to discussion forums, though they may read the contributions of others.
so we've been encouraged to learn a new database technology like NoSQL, analytics and so this course just fitted that learning requirement. I hadn't done any professional learning for a couple of years, although I always feel I try and learn every day if possible, but I hadn't done a course with course work for at least 5 or 6 years.

My primary goal is not to learn, but to complete the course so I can get certified statement of accomplishment. So I definitely set out to watch all the videos and the content provided and try to solve all the assignments, although not necessarily to take part in the additional optional assignments. I am motivated by the reward of getting a certificate. But my learning strengths? I don't think I have anything particular on this one. I always think if I start something then I finish it. So I just want to keep this up.

The invisible learner is motivated by a desire to learn, rather than to receive accreditation or to complete a course. They often are highly regulated and are able to carefully match their engagement to their needs and motivation. Their behaviour may fit perfectly with their own learning objectives, but is not 'ideal' for the course facilitators or even for the other learners. They may be passive in their engagement and driven by a desire for content and

skills. Consequently, they typically do not undertake the activities or assessments and do not contribute to the discussion forums.

It's very important for me to improve my knowledge base because I want to ensure that I am keeping up to date with the latest ideas and thinking. The MOOC is related to my profession. But I did it, not because I had to, but because I was interested in expanding my knowledge and my skill set. I'm a fairly independent learner and feel like I am good at knowing what I need to do in order to learn the content and skills that I want to learn. …When I need to learn something, I will usually try to do it myself, usually with the help of Google and textbooks rather than to seek out another person, or to find a formal training opportunity. I have used those kinds of 3 avenues. I rely a lot on academic literature for things of a technical nature and I also buy a lot of books.

The socialiser, analogous to the invisible learner, is not motivated by a desire to complete the course or the prescribed activities. They similarly are able to chart their own engagement with confidence. They may undertake some activities. However, their preliminary focus is collaborating with other participants, by contributing to the discussion forums.

The MOOC is more of a personal curiosity than a real work requirement. I'm doing it for myself. Work know that I'm doing it, but it's not a recommended thing on the company, so I'm doing it out of interest. I think that the way I wanted to approach the MOOC was just to follow what interested me, and not worry too much about trying to keep a complete overview of the area. I wanted to find appropriate tools, and tools that can be used in a timely manner. I still completed a couple of the assignments, but I wasn't that worried that I didn't keep going right to the end.

I realised that the discussion aspects were among those that suited me best because, as I saw it, I could read a book and get the same content or at least I could get equivalent content, I could watch YouTube videos and the same kind of thing. The things that were really different were the motivation from doing things with a group of people and the chance to talk things out about issues. In my personal experience, being able to talk things out has been really useful to me. So that's probably the predominant way I learn in MOOCs now.

Making sense of the learner stories
While research and researchers typically try to make sense of particular situations, creating models of behaviour and learning, one of the most defining, yet poorly understood, features of a MOOC is the variability in the degree to which learners engage in the course. A number of studies have sought to identify the individual-level factors that influence successful learning in MOOCs. A learner's geographic location affects not only accessibility to MOOCs, but also their interest in topics (Liyanagunawardena, Adams, & Williams, 2013), with demographic information positioned as a mediating factor to explain behaviour in a MOOC (Skrypnyk, de Vries, & Hennis, 2015). Confidence, prior experience and motivation (Littlejohn et al., 2016; Milligan et al., 2013), and a learner's occupation (de Waard et al., 2011; Hood, Littlejohn, & Milligan, 2015; Wang & Baker, 2015) further have been found to mediate engagement. A relationship between learners' goals and their learning outcomes has also been identified (Kop, Fournier, & Mak, 2011; Littlejohn et al., 2016), while there is also evidence that a learners' prior education experience influence their retention in a MOOC (Emanuel, 2013; Koller, Ng, Do, & Chen, 2013; Rayyan, Seaton, Belcher, Pritchard, & Chuang, 2013).

The massive number of learners who participate in the wide-ranging courses on offer make fitting a single narrative of learning in MOOCs, or attempting to understand and measuring learning in relation to a single variable, challenging. What the learner stories above demonstrate is the range of behaviours, attitudes and motivations at play among MOOC participants. Indeed, the personal vignettes are all taken from learners participating in the same MOOC and yet each learner is characterised by an individual journey.

What does emerge from these stories are a range of "factors" that appear to influence the nature of engagement, and ultimately learning that occurs. Of these, three factors – motivation, self-regulation, environment and space, socialisation – appear critical to an individual's engagement, but often overlooked by researchers. These three factors fit closely with Illeris' (2007) fundamental processes of learning framework. Illeris suggests that to understand any learning, it is necessary to consider how an individual learner draws upon his or her existing cognitive frameworks, personal ontologies and social capital to navigate the experiences, resources, tools and spaces made available to them. How is the learner and his or her learning activity situated within their broader contexts of action?

Motivation
Research suggests that there is considerable variety in learners' motivations for enrolling in a MOOC (Littlejohn, et al. 2016). Research on early MOOC participation (2011-2014) identified that learners' typically were motivated by interest in the topic, access to free learning opportunities, the desire to update knowledge or to advance professionally, the opportunity to engage with world-class university content, and the wish to gain accreditation and new credentials (Davis, Dickens, Leon, del Mar Sanchez Vera, and White, 2014; Wintrup, Wakefield, and Davis 2015). Learning out of interest, rather than learning to gain credentials, was found by Christensen et al. (2013) to be the primary reason for MOOC enrolments, followed by the opportunity to "gain skills to do my job better" (43.9%). These sorts of learners were influenced to learn through their own intrinsic motivation.

More recently, a new wave of MOOC learners are attracted by different sorts of incentives, and in particular to improve performance at work or gain qualifications. MOOC developers have been adept at recognising and providing for this new (and lucrative) market of professional development (Grossman, 2013) and accreditation.

An increasing number of MOOC platforms and providers have used learners' growing motivation to up-skill professionally and to gain some form of credential or accreditation to generate a new income stream from MOOCs. While many MOOCs still offer a free option, learners can pay a premium for a course certificate. For instance, Coursera introduced its 'Signature Track' in 2013, which enabled learners to take an assessment to earn a course certificate for a fee of $49. Coursera has since expanded this model as 'Specialisations', a series of four to six MOOCs that learners complete in order to earn a certificate, costing between $300 and $600. Udacity similarly offers the fee-based nano degree while the Harvard-MIT edX platform offers MicroMasters credentials in conjunction with 14 universities. Student needs and motivations are directly influencing MOOC designs while MOOC providers' need to generate and income is tapping into learner's motivations.

Self regulation
Self-regulation refers to 'self-generated thoughts, feelings, and actions that are planned and cyclically adapted to the attainment of personal goals' (Zimmerman, 2000, p. 14). Positive correlations between self-regulated learning behaviour and academic achievement have been found in research both of formal offline learning (Pintrich & de Groot, 1990;

Zimmerman & Schunk, 2001) as well as online more informal learning (Barnark-Brak, Lan, & Paton, 2010). The ability to self-regulate one's learning is mediated both by personal-psychological factors as well as contextual-environmental factors. Previous research by the authors identified significant differences in self-regulated learning behaviour between learners from different contexts and professional roles (Hood et al., 2015).

The authors' research into self-regulation in MOOCs has further identified important relationships between a learner's motivation and goal orientation and their ability to self-regulate their learning. Learners identified as exhibiting highly self-regulating behaviour were less concerned about outward measures of performance in MOOCs, preferring to concentrate on developing knowledge and expertise that was relevant to their professional needs (Littlejohn et al. 2016). In contrast, learners who exhibited lower self-regulate learning behaviours were more likely to be motivated by traditional, extrinsic measures of performance as such course completion.

The four learning types and personal narratives above clearly identified the differences among learners' ability to self-regulate their learning. The largely self-directed nature of MOOCs, where learners are responsible for driving their own learning and engagement, typically with minimal support from teachers or tutors, is better suited to those who have the necessary knowledge and skills to drive their own learning.

These three learners were able to employ a range of learning behaviours and to pursue different pathways, in order to meet their different goals and outcomes. The socialiser, the conventional learner and the invisible agent are all able to shape their learning in order to reach their desired goals. While each engages in a different learning journey, each of these learner types have the cognitive and social capital to be able to employ a range of learning behaviours and to pursue different pathways, in order to meet their individual goals and outcomes. In contrast, the cautious learner mostly likely has less experience having to regulate and drive their own learning and lacks the needed capital to be able to chart the learning journey that is best matched to their own needs and goals.

Cottom (2014) has arguesd that online learning systems re-designed and configured to 'the norm' of a self-motivated, highly able individual who is 'disembodied from place, culture, history, markets and inequality regimes'. That is, MOOCs tend to cater for those who have the social and educational capital to engage with the learning opportunities. The corollary being that while on one level MOOCs are able to open up access to learning and education, that is acting as an "education emancipator", the reality is that often serve some learners much better than others. The learners who are best able to navigate the learning experience in MOOCs are those that already have considerable learning experience and have the necessary skills, knowledge and dispositions to be able to regulate and drive their own learning.

Environment and space
MOOCs typically are conceptualised as decontextualised learning experiences, with little thought given to the environments and spaces of the individual learners. Learning and resultant knowledge construction exists within and is enabled in part through an individual's participation within their context of practice, as well as through interaction and engagement with the resources (material and human) available in that context (Lave & Wenger, 1991). That is, while anyone, anywhere is able to access a MOOC, their learning experience is informed and shaped by their own learning environment which is not a single static entity but rather is comprised by multiple, interconnected systems, including individual personal

ontologies and environments and the resources available in the MOOC, including interactions with others. Consequently, environment and space play a substantial, but too often unrecognised role, in learning in MOOCs.

Barron (2006), in her work on learning ecologies, describes the importance of understanding the multiple environments in which technology-enabled learning occurs:

> Understanding how learning to use technology is distributed among multiple settings and resources is an increasingly important goal. …often learning was distributed over several settings and across many types of resources. More experienced students accessed a greater number of resources both in and out of school. Individual differences in the range and types of learning resources utilized were found even when physical access to computers and to the Internet were the same, suggesting that differences were due to variations in interest or resourcefulness. The results also suggested critical interdependencies between contexts. (2006, pp. 194-196).

As the learning stories illustrated, different learners chose to engage with the different resources they had access to, both as part of the MOOC and beyond it, in very different ways.

To fully understand the importance of environment and space in MOOCs it is necessary to consider not only how the human actors or learners engage with and through them, but also how the role of nonhuman materials and entities enter, engage in, and shape the spaces. The social shaping of technology and physical objects through language, practice and interactions (sometimes called socio-materiality) provide useful lenses for examining the interdependencies of MOOCs and their contexts. Kling and Courtright (2003, p. 223) position online sites from a sociotechnical perspective as being:

> ... structured sociotechnically, co-configured not only by the constraints and affordances of the technologies involved but also – and primarily – by social, economic, and institutional factors.

This is similar to Fenwick's (2015) socio-materiality perspective, in which she suggests that:

> What socio-material approaches offer to educational research are resources to systematically consider both the patterns as well as the unpredictability that makes educational activity possible. They promote methods by which to recognise and trace the multifarious struggles, negotiations and accommodations whose effects constitute the 'things' in education: students, teachers, learning activities and spaces, knowledge representations such as texts, pedagogy, curriculum content, and so forth. (p.84)

Thus, understanding learning in MOOCs requires the ability to identify, examine and interpret the intricate relationships that emerge between learners, technology, content, and environments, with each actor actively shaping and influencing the patterns of behaviour and structuring the learning that arises. The socialisation between individuals and groups of individuals and how this socialisation process shapes and is shaped by the technological infrastructure is a much-discussed element of learning in MOOCs, however, the learner stories demonstrate the wide ranging nature of socialisation occurring in MOOCs.

Socialisation
The learner stories identified very different approaches to socialisation and interaction in MOOCs. Socialisation and levels of interaction have been the focus of numerous research

studies. This typically stems from the belief that socialisation is a positive learning behaviour and something to be encouraged in MOOCs. Indeed research has identified that peer interactions can support learning and knowledge-building activities (Amo, 2013; Conole, 2013; Hew, 2014; Margaryan et al., 2015), community formation (Warburton & Mor, 2015) and opportunities for help-seeking and peer assistance (Amo, 2013; Guardia et al., 2013; Hew, 2014). Furthermore, a relationship has been identified between learners' participation in discussion forums and course completion (Gillani & Eynon, 2014; Kizilcec et al., 2013; Sinha, Jermann, & Dillenbourg, 2014). However, research has also found that learner discussions and interactions on a MOOC tend to be characterised by decreasing participation over time (Jordan, 2014) and that some conversations are restricted because the students have limited experience and knowledge to drive forward analysis of key concepts (Sinha, Li, Jermann, & Dillenbourg, 2014). Further research has determined that many MOOC learners do most of their learning on their own (see, for example, Littlejohn et al. 2016; Alario-Hoyos et al., 2014).

Indeed the learner stories presented in this chapter clearly show this wide variation in levels of socialisation and interaction with others on a MOOC, as well as the varying motivations for this interaction. For some, particularly learners who tend towards the 'cautious learner' type, community and peer support may provide an important scaffold, offering direction and advice in how to navigate the learning on offer. However, not all learners feel comfortable engaging socially or collaboratively in a MOOC setting (Milligan & Littlejohn, 2016). Another characteristic of discussion forums is that people with similar interests and knowledge may work together, giving rise to a phenomenon termed 'homophily'. While forming small groups or communities online with whom a learner can readily engage and interact can support learning and knowledge development, it can also potentially lead to a narrowing of knowledge and ideas.

Measuring learning; the potential of learning analytics
MOOC platforms are implementing tools that draw on analytics-based systems termed 'learning analytics'. There is a view that using data analytics to gather information about learners' characteristics and motivations can help to design more attractive courses and promote engagement, which may lead to better retention, engagement and learning (Rienties & Rivers, 2014; Ferguson, 2012).

Learning Analytics make use of complex datasets containing multiple data types in various types of analysis, including discourse analysis, where learners' discussions and actions provide opportunity for helpful interventions (Gilliani & Enyon, 2013); semantic analysis, tracing the relationship between learners and learning (Yang et al., 2014); learner disposition analytics, identifying affective characteristics associated with learning (Shum & Crick, 2012); and content analytics, including recommender systems that filter and deliver content based on tags and ratings supplied by learners. These techniques may be useful for learners with low self-regulation who need support with task planning and time management but also run the risk of formulising and over-structuring the learning experience for those learners who exhibit higher levels of self-regulation and want to design their own learning pathway.

Claims of the potential learning analytics is balanced by a degree of scepticism from learning scientists who are concerned that analytics techniques promote a narrow, static view of desired outcomes and norms of behaviour in a MOOC which belie the fluidity, flexibility and socialisation that underpin the learning opportunities on offer. Morozov (2014) suggests that algorithms and analytics are concerned with predictive analysis with little concern for

wider questions of causation, context of consequences. Laru, Naykki, & Järvelä (2014) build on this arguing that the emergent systems focus on predicting progress, rather than promoting learning skills, namely self-regulated learning and collaborative learning. They argue this problem is partly because the systems development has had poor grounding in learning science. Selwyn (2016, p72) suggests that rather than personalising the learning experience, analytics is reinforcing mass customization of education through large systems. This perspective reinforces the idea of the 'student as customer' justifying the use of analytics to customise course designs in ways that allow the maximum number of students to complete a course. This viewpoint contrasts with the idea of 'student as learner' where the goal of analytics is to provide personalised learning support for each student to scaffold their learning. Approaches to learning analytics often are based on analysing student behaviours with the aim of maximising the number of students completing courses. These analytics techniques use behavioural data that easily is measured – for example 'clickbait' data tracing the learners' choices and behaviours in the MOOC platform. Measurement of complex cognitive and affective data on the factors that are important for learning in a MOOC - learner motivation, self-regulation and socialisation - are difficult to measure. Furthermore, these factors have to be considered across the entire environment in which learning takes place, not just the MOOC platform.

There is a danger that narrow approaches to analytics will lead to what Biesta (2007) has termed 'normative validity', that 'whether we are indeed measuring what we value, or whether we are just measuring what we can easily measure and thus end up valuing what we [can] measure'. Some researchers have experimented with analysis of complex behavioural, affective and cognitive factors associated with learning in MOOCs - motivation, self-regulation, socialisation and environment - with limited success. This section examines some of the analytics tools and techniques that show positive outcomes:

Motivation
If MOOCs are a way to support students in learning what they want to learn, then learning success has to be measured in relations to each learner's motivation and goals, rather than against a standardised set of course objectives. Developing analytics that incorporate and utilise learners' motivation and goals is challenging. It will rely, at least in part, on learners' self-identifying their motivations and goals, and as with many measures, self-identification can be problematic. It is possible that a learner may not yet know her motivations or may have multiple motivations. Furthermore, motivations, and accompanying goals, often change over time and are context dependent. As learners' in our own research have identified, their goals and priorities shifted during their participation in a MOOC. Therefore, systems that measure motivation must continually prompt learners to reflect on their motivations for learning and their goals.

'Charting' was an early system that supported learning through specifying and sharing learning goals (Littlejohn, Milligan, & Margaryan, 2011). The charting system was a set of online tools that prompted users to specify their learning goals. Learners were connected with others who had similar goals, creating networks of people who could share information and knowledge resources, and support each other as they learned. However, user tests identified that learners found it difficult to articulate their learning goals and that selecting a goal from a limited drop-down menu was too restrictive. At the same time, free text entry meant that users had to be able to clearly articulate their goals.

More recently, semantic-based systems enable the combining of free text options with pre-defined text entry, providing the user with possible options when she starts typing her

motivations and goals. Despite these technological advances, there remain additional challenges. Learners tend to have a combination of high level, long-term goals and micro-level short-term goals. For some learners, it is challenging to break down long term motivation and goals into smaller, more actionable goals. Also, it is necessary to provide a means for learners' to track and assess their progress towards their given goals.

Recently an analytic tool was developed to monitor socially shared regulation. The 'S-REG' mobile application tool (app) was trialled in collaborative learning, classroom settings (Järvenoja, Järvelä, & Malmberg, 2017). Learners could use the app to record videos of their group learning. These data were captured, annotated and coded to identify instances of co-regulation of motivation during collaborative group work. An advantage of this type of analytics is that it can model motivational data using quasi-ethnographic techniques. However, analysis of these data currently is carried out by researchers, so the analysis is not available in real time.

Work is already underway to build systems based on AI and machine learning that can automatically record, transcribe and code spoken data in real-time (see for example Stahl, 2015; Stahl, Rosé & Goggins, 2017;). However, these systems are still in early stage development. To support and scaffold learners in real time, data would have to be processed using AI methods that do not yet exist. It is likely to be some time before algorithmic codes have this capacity. In the meantime, teacher expertise together with learner intuition is a better way to identify and strengthen motivations.

Self-regulation
The ability to self-regulate one's learning is a critical competency for open, online learning. Analytics tools designed to support self-regulation tend to be focused on individual factors of self-regulation, such as time management. Support on these single factors support students to a limited extent, but there are two key problems with this approach. First, it reduces the complex process of self-regulation to a single component. And second, the analytics systems tend to assume each learner's goal is the same as the course objectives. Yet, as discussed earlier, learners in open, online environments often have their own learning goals, rather than adopting the course goals. This approach to analytics reinforces mass standardisation where large numbers of students are supported so they fit with the course structure and objectives, rather than being supported to make their own learning decisions.

Researchers have experimented with analytics systems that carry out complex analyses using data on factors that influence self-regulated learning. One example of this type of system is Learn B, which has been used in the automotive industry to gather data on factors that influence self-regulated learning at work. These factors include how individuals and groups plan learning goals and the activities people engage in as they work towards these goals. Learn B, is based on similar principles to 'Charting' and acts as a 'developmental radar' allowing learners to identify their learning goals, then connect with relevant people and knowledge based on shared goals (Siadaty et al., 2011). However, the Learn B system uses Social Semantic Web technologies. Users select learning goals from a dropdown menu. Their choices are recorded and analysed using semantic analysis.

The system is based on the assumption that people learn effectively by using strategies that have been effective for others with similar goals. The social recommender systems feeds learners ideas on how they might achieve their goals, based on the learning patterns of other people. Trials of the Learn B system demonstrated that it was useful in helping

learners develop self-regulated learning skills. However, the trials occurred within an automotive company where people were learning sets of pre-determined procedural competencies, which typically require linear forms of learning, rather than the more bespoke, individualised learning pathways that typically occur in MOOCs.

Supporting students in learning how to self-regulate their learning is a complex, resource intensive and long-term undertaking. Self-regulation skills and behaviour must be developed and practiced over time and across a range of different learning contexts. Furthermore, self-regulated learning incorporates numerous facets, and future systems must provide a means for capturing information and supporting students across these different facets.

Socialisation
The examples of analytics systems described earlier illustrate that online learning can be direct, through discussion and group work, or indirect, through knowledge sharing. While discourse analysis is becoming increasingly sophisticated and able to make a range of inferences based on participation, engagement and semantic patterns in online discussion forums, these do not capture the full scope of social learning that can occur online. A particular challenge facing learning analytics attempting to capture knowledge sharing is the oftentacit nature of knowledge, which makes it difficult to capture and codify in ways that enable others to learn.

An analytics system designed to capture and disseminate knowledge in industry is WEKIT (*Wearable Experience for Knowledge Intensive Training*). Industry experts carry out work tasks while wearing the WEKIT tools and it captures their work. Learners can then wear the WEKIT kit while carrying out a similar task and can benefit from viewing, listening to or reading about how and why the expert approached the task in specific ways. The system helps with learning procedural knowledge, such as how to turn off a specialist valve. A head-mounted display is used to overlay an augmented visual interface so the learners can compare their actions with the behaviour of the expert.

The system is based on three-stage process: mapping learning pathways, capturing and codifying knowledge, and making this knowledge available to learners at the point of need. Social Learning Analytics capture and compare data analysing and drawing attention to differences in the behaviours of the learners compared with the experts, supporting them in learning how to carry out new tasks. This system is based on a pre-defined learning pathways, mapped out by experts then developed by software engineers into pathway templates. While these systems are well-suited to facilitating social learning around procedural knowledge construction, dissemination and reconstruction, they struggle with more complex, personal and tacit knowledge, which tends to be rooted in the actions, experience and participation of individuals.

Emerging analysis techniques combine specific affective, cognitive and behavioural data with socialisation data. One example is Epistemic Network Analysis (Shaffer, 2016). Data measured by recording discourse and actions as learners interact in groups and as their knowledge and skills expand. These data are analysed based on each individual's position within a cognitive network. The analysis takes into consideration how the knowledge and skills of each learner fits within the network. Analytics are used to examine trace the development of the skills and knowledge of each individual learner and how this fits within the overall 'epistemic network' as they interact with peers and experts. According to Shaffer (2016, p.9), measuring and analysing the structure of connections among cognitive factors is more important than measuring those elements in isolation. Network models

compare how novice learners interact in the network and analyse the contributions of each individual and how these contributions fit within to the network as a whole.

Conclusions

This chapter has explored the complexities and incongruities of scale, diversity and personalisation through the lens of the varied ways in which learners approach and engage with MOOCs and the resulting variation in learning that occurs. MOOCs are somewhat paradoxical. By name, they reference the large number of potential learners and the rhetoric surrounding MOOCs frequently positions them as disruptive democratisers, that open up access to education and present new learning opportunities. However, the reality is somewhat different. The majority of MOOCs continue to follow traditional academic paradigms and conventions, employing traditional measures of quality and applying conventional approaches to what constituted attainment, success and learning.

By viewing MOOCs through the perspective of the learner, this chapter has emphasised the highly individualised nature of engagement in MOOCs, where for many learners, learning is non-linear and the desired mode of engagement does not follow a standardised route. Instead, learning (as learning theory would suggest applies not only to open, online education but any form of learning) is deeply informed by the individual learner; their personal ontologies, motivations and goals, contexts of action, and the learning opportunities with which they are presented. Hence, as our four learner stories suggested, there are multiple ways to engage and learn in a MOOC.
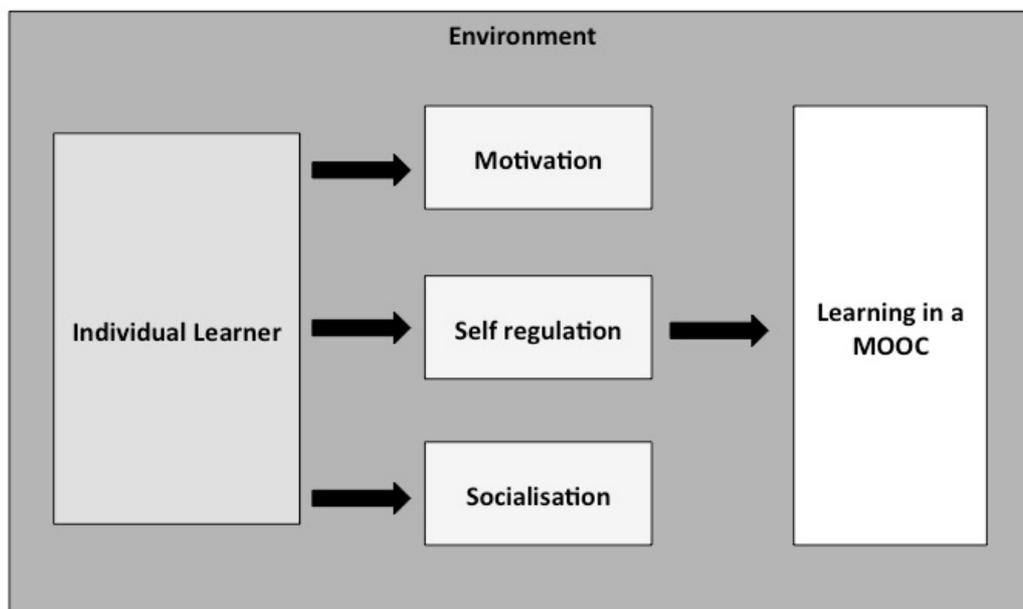

Figure 2: The nature of learning, including influencing and mediating factors, in a MOOC

The learner stories further identified that three factors – motivation, self-regulation, socialisation – mediate learning and engagement in an environment (Figure 2). The environment, however, expands across the various physical and virtual sites within which the learner operates. It is not simply the online environment of the MOOC, and ways in which a learner engages with the learning resources provided on it, but includes complex interactions across a range of sites and contexts in which they are situated.

The distributed learning environment of MOOCs often is overlooked by education providers and learning designers. The online environment, incorporating the platform and the content, instructional design, and pedagogy of the individual course typically is recognised as a factor that shapes learning and engagement. However, the broader environments in which MOOCs are situated, encompassing the individual contexts of each learner, often receive limited attention. The importance of the "out-of-MOOC" learning environments becomes particular apparent when considering that while MOOC participants may technically engage in learning activity online, they most likely will be consolidating that learning and utilising and enacting the new knowledge they have developed in a different (online or offline) context. Therefore, learning is always situated across and influenced by multiple contexts.

For the full democratising power of learning in MOOCs to be realised, two key conditions need to be met. Firstly, it is critical to recognise the individual as the driver of learning, engagement and experience in a MOOC. MOOCs have a unique opportunity to move beyond traditional educational paradigms that are focused on standardisation, linear progressions, and pre-determined, unchanging measure of what constitutes learning and success. In order to move beyond conventional norms of traditional education, secondly it is important that MOOCs develop the support structures and learning analytic tools to facilitate this personalisation and to accommodate the diversity that comes with it.

However, currently, as described in this chapter, too many learning designs and analytics systems personalize learner support in relation to pre-defined learning pathways, rather than in relation to the individual needs or goals of the learner. Often they default to conventional metrics and measures of successful learning and quality, without fully recognising what is new and potentially different about learning in MOOCs. It is necessary to fully engage with the unique nature and opportunities presented by open, online education, together with the unique needs and agendas of the learners who are engaging with these learning opportunities. Its critical to move from the current focus of analytics systems that support learners to behave as an 'ideal student' or to use analytics to alter course designs that allow the maximum number of students to pass the assessment. In the future we should develop and implement analytics systems that empower learners to follow their own motivations and goals. These systems have to be sufficiently intelligent to flex course designs to fit the motivations and goals of each learner, rather than the student having to adapt to the norms of a course designed for the masses using analytics.

Developing analytic tools that address factors such as motivation, self-regulation and socialisation, which this chapter has identified as being so pivotal to learning, is a challenging prospect. Early systems have been developed and trialled in both formal education and workplace learning contexts. There are opportunities for the education sector to learn from the work being developed in other sectors, such as automotive engineering and the energy sector where learning analytics, AI and machine learning techniques are advancing rapidly. However, it seems that while other industries are making use of these new technologies and the opportunities they present to redefine traditional processes and paradigms, education is yet to fully recognise their potential. Open, online education presents an opportunity to converge learning analytics, AI and machine learning with the best of what we know about the science of learning to enhance the learning opportunities offered in MOOCs.

While the potential of technology to "revolutionise" technology is ever present, it is necessary to place some caveats around it. It is critical not to forget the human element of learning and education, to recognise that at its heart learning is an interaction and exchange

between people, built on relationships, which are structured by the varied contexts in which people learn. When designing any learning, it is necessary to not lose sight of the fundamental questions of what constitutes good education and for what are we educating.

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