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Context counts: How learners' contexts influence learning in a MOOC

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A B S T R A C T

Massive Open Online Courses (MOOCs) require individual learners to self-regulate their own learning, determining when, how and with what content and activities they engage. However, MOOCs attract a diverse range of learners, from a variety of learning and professional contexts. This study examines how a learner's current role and context influences their ability to self-regulate their learning in a MOOC: Introduction to Data Science offered by Coursera. The study compared the self-reported self-regulated learning behaviour between learners from different contexts and with different roles. Significant differences were identified between learners who were working as data professionals or studying towards a higher education degree and other learners in the MOOC. The study provides an insight into how an individual's context and role may impact their learning behaviour in MOOCs.

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1. Introduction

Early enthusiasm, both from researchers and the mainstream media, surrounding the potential for Massive Open Online Courses (MOOCs) to 'revolutionise' and 'democratise' education has been replaced by growing concern that MOOCs have not had as profound or as fast an impact on education as initially anticipated (Daniel, 2012; Gillani & Eynon, 2014; OBHE, 2013). The reasons may be related to MOOC implementation (Mackness, Mak, & Williams, 2010). MOOCs are characterised by open access, learning at a distance (online) and scale. Key features include free registration, open access to learning (regardless of prior qualifications), a large and diverse learner body who not only have different backgrounds but also wide ranging motivations for enrolling in a course, and the absence of a single, linear learning progression followed by all students on a course (Breslow et al., 2013; Gaebel, 2013).

Despite these novel features, MOOCs tend to be structured as adaptations of conventional HE courses, adopting the same procedural metaphors as face-to-face courses but using technology, such as video recordings of lectures, to achieve scale (Fini, 2009). A study of the instructional design of 76 MOOCs revealed that MOOC design primarily concentrates on the organisation and presentation of course material, missing opportunities for new forms of interaction and feedback involving massive, diverse groups of people (Margaryan, Bianco, & Littlejohn, 2015). Investigations of learning in MOOCs have focused on what can easily be measured at scale, such as progression, retention and completion rates (Liyanagunawardena, Adams, &

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Williams, 2013), which give an understanding of the whole cohort but provide little insight into the behaviour of the individual. The openness of MOOCs and the resultant potential diversity of learners, each with different base-line knowledge and prior experience, makes the investigation of individual learners particularly important. More research is required, which focuses on the unique nature of learning and learners in MOOCs and examines the new methods of knowledge production and learning that MOOCs can support (Gillani & Eynon, 2014; Milligan, Littlejohn, & Margaryan, 2013; Veletsianos, Collier, & Schneider, 2015).

Learning in a MOOC differs from the pre-determined structure of conventional higher education (HE). The absence of interaction between the instructor and learners on a MOOC requires individuals to self-regulate their own learning, determining when, how and with what content and activities they engage (DeBoer, Ho, Stump, & Breslow, 2014; Kop, 2011; Mackness, 2013; Milligan & Littlejohn, 2014). Studies suggest that learners who are better able to self-regulate their learning, in either formal or informal settings (e.g. to support learning in the workplace), employ more effective learning approaches in online settings (Bernacki, Aguilar, & Byrnes, 2011). The ability to self-regulate one's learning is shaped by both personal-psychological and contextual factors (Zimmerman, 2000). Cognitive, affective and behavioural factors, such as interest in a task, self-efficacy, the ability to employ a range of learning strategies, self-reflection and self-satisfaction, all impact learning in a MOOC (Milligan & Littlejohn, 2015).

This study explores in detail how learners self-regulate their learning in a MOOC. The course was the 'Introduction to Data Science' MOOC offered by the University of Washington through Coursera. Participants in the MOOC came from diverse contexts, encompassing data science professionals, HE students and others learning for more general interest. Given the limited research to-date examining the effect of learner context on the learning strategies and behaviours employed in a MOOC, this study was structured around the research questions: *What self-regulated learning strategies do learners apply in a MOOC? and, How does a learner's current role influence their ability to self-regulate their learning in a MOOC?* The paper begins with an examination of the literature on self-regulated learning (SRL) in the online setting and how this literature relates specifically to MOOCs. This is followed by a description of the methods used to investigate the research questions, including an overview of the survey instrument employed in the study. The data analysis process and findings are then presented and discussed. The paper concludes by summarising the key findings and reflecting on the limitations of the study as well as potential directions for future research.

2. Literature review

MOOCs offer open, online learning at a massive scale. They operate as non-formal learning spaces (Colley, Hodkinson & Malcolm, 2002), where individual participants choose how, when and in what ways they engage. Typically content is disseminated through video-recorded lectures, which are accompanied by automated assessments and online discussion forums where learners can interact with other participants (but not the instructor). Researchers interested in investigating learning in MOOCs have utilised the vast amounts of data generated as learners participate in learning in MOOC environments (Breslow et al., 2013; Kizilcec, Piech, & Schneider, 2013), which enables tracking of the frequency and focus of learner engagement. Much of the research on learner behaviour has focused on understanding why completion rates are low (Jordan, 2014; Perna et al., 2014; Weller, 2014). The relationship between completion rates and learners' educational background, gender and geographic location have all been investigated (Breslow et al., 2013; Guo & Reinecke, 2014; Kizilcec et al., 2013). Yet there is little conclusive evidence that any of these factors explain learner behaviours and choices. Further research has investigated the connection between the nature of learners' participation in the online discussion forums and completion rates (Gillani & Eynon, 2014). This work uncovers the complexity around learner motivations, actions and behaviours in non-formal contexts. Not every MOOC participant is motivated to complete the course.

While online learning analytic data provides new insight into learners' actions in a MOOC, they provide little understanding of the learning dispositions or behaviours individuals bring to a MOOC, or how these characteristics help to shape their engagement and learning. The non-formal nature of MOOCs and the resulting non-linear navigation of most learners (Guo & Reinecke, 2014) combined with their massive scale, which limits personal interaction with the tutor, requires individual learners to have the necessary dispositions to structure their learning activities independently (Kop, 2011; Milligan & Littlejohn, 2015). However, with the broad range of participants MOOCs attract, there is wide variance in the ability of learners to self-regulate their learning (Milligan et al., 2013). Similarly, Gašević, Kovanović, Joksimović, and Siemens (2014) call for studies that explore learner behaviour in MOOCs arguing that because levels of tutor support are lower than in traditional (formal) online courses, there is a need for greater emphasis on the individual learner's capacity to self-regulate their learning.

Studies of self-regulated learning first emerged in offline (face-to-face) contexts in formal education. 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). Zimmerman identified three phases of self-regulated learning – forethought, performance and self-reflection – and a number of sub-processes associated with each phase. The ability to self-regulate one's learning is mediated by both personal-psychological factors (cognitive and affective) and contextual-environmental factors. Self-regulated learning is not a fixed characteristic and an individual's self-regulation behaviour may change in different contexts. For example, in learning situations where the learner is more motivated and interested or in contexts where the learner feels more confident he or she may be more self-regulated (Pintrich, 2000).

Self-regulation has been positively associated with academic outcomes in formal, offline learning contexts (Pintrich & de Groot, 1990; Zimmerman & Schunk, 2001) and a number of studies have investigated the role that SRL plays in online learning environments (for a comprehensive overview see Bernacki et al., 2011). Azevedo and Cromley (2004) found that providing self-regulated learning training to learners supported both their performance and learning processes in online settings. A study of individuals participating in an online degree programme identified five distinct profiles of self-regulated learning, ranging from super self-regulators to non- or minimal self-regulators (Barnard-Brak, Lan, & Paton, 2010). The authors further determined significant differences in academic achievement by learners' self-regulated learning (SRL) profiles. Other studies have attempted to identify the sub-processes of self-regulated learning that are particularly important for engagement with online learning opportunities. Cheng and Chau (2013), investigating the role of self-regulated learning in e-portfolios, identified five sub-processes that were associated with higher achievement – elaboration, organisation, critical thinking, metacognitive self-regulation and peer learning. In an experimental study Chang, Tseng, Liang, and Liao (2013) found that students in an online learning group demonstrated significantly higher self-regulation and more positive attitude toward learning motivation, self-efficacy and subject values than students in the offline learning control group. There have been few studies to date examining the role that SRL plays in influencing MOOC participation. A recent study investigating self-regulation of learners with (self-reported) high and low levels of SRL in a MOOC (Milligan & Littlejohn, 2015) identified four SRL sub-processes where differences were noted between high and low self-regulators. These sub process include goal setting, self-efficacy, learning and task strategies, and help-seeking strategies.

While studies indicate the importance of self-regulated learning for both engagement and achievement in online learning activities, the lack of research focussing specifically on MOOCs is problematic. MOOCs differ from traditional online learning courses in several key respects. Their massive scale restricts the level of individual direction and support that can be provided, which requires individuals to take greater responsibility for their learning. Furthermore, MOOCs attract a broad cross section of participants, each with different backgrounds and motivations for undertaking the course. This diversity potentially leads to different levels of engagement and varying need for support (DeBoer, Ho, Stump, & Breslow, 2014). MOOCs represent a non-formal learning context, and lack the pre-established, sequential progression of many formal online learning courses. Analysis of learner behaviour on four MOOCs determined that certificate earners viewed on average only 78% of learning sequences, completely skipping 22%, and navigation backjumps from assessments to lectures were more common than lecture-to-lecture backjumps (Guo & Reinecke, 2014), highlighting the non-linear navigation of participants. Previous research examining self-regulated learning in non-formal contexts suggests that the ability of learners to self-regulate their learning is just as important, if not more so, in these contexts compared with more formal learning situations because the onus is placed on the learner to determine their own learning outcomes and to regulate their actions and behaviour to achieve these (Fontana, Milligan, Littlejohn, & Margaryan, 2015; Milligan & Littlejohn, 2014; Redecker et al., 2011). This study builds on previous research into self-regulated learning in non-formal and online contexts to investigate both the SRL sub-processes learners employ in MOOCs and to examine whether learners' current contexts and roles influence whether and how they self-regulate their learning.

3. Study context

The 'Introduction to Data Science' MOOC [https://www.coursera.org/course/datasci] from the University of Washington was an eight week course offered on the Coursera platform. The course introduced participants to the basic techniques of data science and was intended for people with intermediate-level programming experience and familiarity with databases. Alongside weekly readings, video lectures and short quizzes, the MOOC also had four programming assignments. Approximately 50,000 learners, from 197 countries were enrolled in the MOOC. Recruitment for the study was achieved initially through completion of the survey distributed by an announcement sent to all course participants, and posted on the course message board in week 2 of the course.

4. Methodology

The survey was a slightly modified version of a published, validated instrument designed to measure self-regulated learning in adult learners in informal learning contexts (Fontana et al., 2015). The instrument was revised as follows, with modifications minimised to maintain the balance and focus of the original. The language of the instrument was simplified to reflect the international nature of the audience. Items were reviewed to assess their suitability for use within the MOOC context and reworded if necessary. Three items that did not load for any factor in the original instrument were replaced. This last amendment allowed the identification of an additional factor (F5: help-seeking), which had not been possible in the original instrument.

Table 1
Phases and sub processes included in the SRL instrument.

Forethought	Performance	Self-reflection
Goal setting	Learning and Task strategies	Self-satisfaction
Self-efficacy	Help seeking	Self-evaluation
Task interest value		

The instrument is structured into three sections reflecting Zimmerman's (2000) three phases of self-regulated learning – forethought, performance and self-reflection. Each section measures a range of SRL sub-processes (see Table 1). The sub-processes, which were drawn from the work of both Zimmerman (2000) and Pintrich, Smith, Garcia, and McKeachie (1991), were selected for their relevance to a more informal learning context. The instrument consisted of a total of 42 items; 17 measuring forethought, 19 items measuring performance and 6 items measuring self-reflection.

788 learners fully completed the survey. Respondents were from 79 countries. 303 respondents were currently employed as a data professional, 141 were studying for a higher education qualification, 59 were both currently employed as a data professional and studying for a higher education qualification, and 285 were neither employed as a data professional nor studying for a higher education qualification. Overall SRL scores for each participant were calculated by adding the responses for each of the 42 items, with a minimum possible score of 42 and a maximum score of 210. The minimum and maximum scores observed were 45 and 210, respectively, with an average of 145.0 (SD 24.6).

The dataset was analysed with the SPSS software package (IBM Corporation, Armonk, NY, USA). Statistical analysis was conducted to confirm the internal reliability of the instrument (Cronbach's alpha) and convergent validity (Pearson correlation). Exploratory factor analysis was undertaken to determine the factor structure of the whole instrument in order to identify the SRL sub-processes that emerged in the specific context of this study. The decision not to retain Zimmerman's three phases in the analysis stage results from the findings of previous studies of self-regulated learning in informal learning contexts, which suggest that in informal learning contexts the three phases tend to occur iteratively rather than sequentially (Fontana et al., 2015; REFERENCE 6 REMOVED FOR BLIND REVIEW). T-tests were conducted on each of the identified factors

Table 2
Component matrix (8 components extracted): exploratory factor analysis for SRL scale.

Item	1	2	3	4	5	6	7	8
3. I set goals to help me manage studying time for my learning	.827							
2. I set short term goals as well as long term goals	.781							
4. I set realistic deadlines for learning	.734							
8. I organise my study time to accomplish my goals to the best of my ability	.724							
1. I set personal standards for performance in my learning	.606							
7. When planning my learning, I use and adapt strategies that have worked in the past	.401							
15. My past experiences prepare me well for new learning challenges		.668						
17. I feel prepared for the demands of this course		.663						
14. I feel that whatever I am asked to learn, I can handle it		.654						
12. I can cope with learning new things because I can rely on my abilities		.645						
13. When confronted with a challenge I can think of different ways to overcome it		.594						
16. I meet the goals I set for myself in my learning	.475	.569						
21. I think about what I really need to learn before I begin a task			.605					
22. I create my own examples to make information more meaningful			.583	.408				
5. I ask myself questions about what I am to study before I begin to learn			.572					
38. I ask myself if there were other ways to do things after I finish learning			.560					.464
20. I change strategies when I do not make progress while learning			.554					
18. I try to translate new information into my own words			.529					
29. Whenever I read or hear an assertion when learning, I think about possible alternatives			.517					
6. I think of alternative ways to solve a problem and choose the best one		.416	.450					
19. I ask myself how what I am learning is related to what I already know			.422			.405		
39. I think about what I have learned after I finish			.412			.408		.410
25. When I am learning, I combine different sources of information				.725				
26. I try to apply my previous experience when learning				.680				
24. When I am learning, I try to relate new information I find to what I already know				.679				
23. I read beyond the core course materials to improve my understanding				.600				
27. During learning I treat the resources I find as a starting point and try to develop my own ideas from them				.576				
28. I try to play around with ideas of my own related to what I am learning				.567				
32. I ask others for more information when I need it					.885			
30. When I do not understand something I ask others for help					.883			
33. I get someone to help me when I need assistance with my learning					.882			
31. I ask other learners questions when I am uncertain about something					.877			
42. I try to understand how what I have learned impacts my work/practice						.744		
40. I often think about how my learning fits into the bigger picture of my work practice						.691		
41. I consider how what I have learning relates to my peers						.626		
10. I am interested in the topics presented in this course							.770	
11. The learning that I undertake is very important to me							.744	
9. I think I will be able to use what I learn in the future							.731	
34. The most satisfying thing for me in this course is trying to understand the things I learn as thoroughly as possible								.546
37. I know how well I have learned once I have finished a task								.516
35. I like opportunities to engage in tasks that I can learn from								.449
36. I prefer learning that arouses my interest, even if it is challenging		.433						.442

Varimax with Kaiser Normalisation.
Rotation converged in 8 iterations.
61.75% total variation explained.

(sub-processes) to determine whether there were any statistically significant differences in the self-regulatory behaviours of learners from different contexts (i.e. working in the data science field, studying for a HE qualification).

5. Findings

The internal reliability of the instrument was measured by calculating Cronbach's alpha of the 42 SRL scale. Cronbach's alpha was .945, indicating the strong internal validity of the scale.

The underlying structure of each of the scales was investigated using exploratory factor analysis (de Winter, Dodou, & Wieringa, 2009). The analysis uncovered an 8 factor structure (Table 2) (42 items; Cronbach's alpha .945; total variance explained 61.75%).

The eight factors have been identified as representing the following SRL sub-processes.

- F1: ‘goal setting’ (7 items; Cronbach's alpha .863; total variance explained 31.65%). This factor relates to a learner's ability to set both short term and longer term learning goals and to plan their learning and undertake strategies that enable them to reach their goals.
- F2: ‘self-efficacy’ (8 items; Cronbach's alpha .843; total variance explained 7.70%). This factor is associated with the extent to which an individual feels confident in their ability to engage with and complete the learning activities offered on the MOOC.
- F3: ‘task strategies’ (10 items; Cronbach's alpha .867; total variance explained 5.58%). This factor encompasses the ability of the learner to plan their learning and to identify and employ learning approaches that will enable them to learn. It also incorporates the ability of learners to adjust their strategies and plans throughout their learning journey.
- F4: ‘learning strategies’ (6 items; Cronbach's alpha .843; total variance explained 4.93%). This factor refers to the ability of learners to integrate the new knowledge they are gaining with their existing knowledge and experience and to develop their understanding of particular topics and ideas.
- F5: ‘help seeking’ (4 items; Cronbach's alpha .925; total variance explained 3.75%). This factor addresses how learners engage with other people in order to support their learning.
- F6: ‘self-satisfaction and evaluation’ (5 items; Cronbach's alpha .812; total variance explained 2.90%). This factor reflects how learners connect what they are learning with their own current context, assessing how their learning relates to their wider work or educational practice.
- F7: ‘task interest’ (3 items; Cronbach's alpha .765; total variance explained 2.68%). This factor refers to learners' interest in the material they are learning and the importance of their learning to their current and future activities.
- F8: ‘learning challenge’ (6 items; Cronbach's alpha .812; total variance explained 2.55%). This factor reflects the extent to which learners are willing to engage and the sense of fulfilment they receive from engaging in challenging learning activities and their ability to think critically about their learning.

The 8-factor structure is closely aligned with the SRL sub-processes identified by Zimmerman and Pintrich as well as those identified by Milligan and Littlejohn (2014) in the context of a MOOC. Self-evaluation did not emerge as an independent factor. The individual items load evenly between F.3 ‘task strategies’ and F.8 ‘learning challenge’. Task and learning strategies emerged as discrete factors. Task strategies is connected to the ability of the learner to plan and adjust the strategies and approaches they are adopting whereas learning strategies refer to ability of learners to build new knowledge and develop their understanding. These differences in factor distribution may be connected to the decision to include all 42 items within a single factor analysis, rather than maintaining Zimmerman's strict 3-phase division.

5.1. Correlations

The survey instrument was also tested for convergent validity, to examine the relationship between individual factors. Correlation analysis was conducted between the eight factors identified by the principal component analysis (F1–F8) (Table 3).

Table 3
Pearson Correlation between self-regulated learning sub-processes.

	F.1	F.2	F.3	F.4	F.5	F.6	F.7	F.8
F.1	1	.60**	.57**	.47**	.28**	.51**	.38**	.54**
F.2		1	.63**	.57**	.18**	.53**	.50**	.68**
F.3			1	.73**	.30**	.74**	.38**	.76**
F.4				1	.25**	.61**	.40**	.66**
F.5					1	.25**	.15**	.26**
F.6						1	.46**	.71**
F.7							1	.49**
F.8								1

**p < .001.

In keeping with the findings of previous studies (Fontana et al., 2015), there is a significant correlation between each of the SRL sub-processes.

5.2. T-tests

Independent-samples t-tests were conducted to determine whether there were significant differences in the overall SRL scores and the individual SRL sub-processes between learners holding different roles and in different contexts. The analysis identified significant differences in both the overall SRL scores and the scores for some of the sub-processes in learners who were employed as data professionals and those learners who were currently studying for a HE qualification (see Tables 4 and 5).

Table 4 shows that the average overall SRL scores of learners who were employed as data professionals were significantly higher ($M = 147.8$, $SD = 23.8$) than learners who were not employed as data professionals ($M = 144.3$, $SD = 25.1$); $t(786) = 1.99$, $p = .05$.

A significant difference between these two groups of learners was also identified in three SRL sub-processes – self-efficacy, task strategies and self-satisfaction and evaluation. Data professionals had significantly higher self-efficacy scores ($M = 31.4$, $SD = 5.0$) than learners who were not employed as data professionals ($M = 30.0$, $SD = 5.6$); $t(786) = 3.75$, $p = .00$. Similarly, the independent-samples t-test determined a significant difference in the task strategy scores for data professionals ($M = 34.0$, $SD = 7.3$) and learners who were not employed as data professionals ($M = 32.8$, $SD = 7.5$); $t(786) = 2.15$, $p = .03$ and in the self-satisfaction and evaluation scores of data professionals ($M = 17.9$, $SD = 4.0$) than learners who were not employed as data professionals ($M = 17.3$, $SD = 4.1$); $t(786) = 2.36$, $p = .02$. These results suggest that the professional roles and contexts of learners in a MOOC influence their overall self-regulative behaviour as well as three SRL sub-processes.

The independent samples t-test results depicted in Table 5 indicate that there were significant differences in the overall SRL scores of learners studying for an HE qualification ($M = 149.9$, $SD = 25.2$) than learners who were not employed as data professionals ($M = 145.8$, $SD = 25.1$); $t(786) = 2.189$, $p = .03$. Similarly to the data for learners working as data professionals, there were significant differences in the scores for learners currently undertaking a HE qualification in four SRL sub-processes – task strategies, self-satisfaction and evaluation, task interest and learning challenge. Learners studying for a HE qualification had significantly higher task strategy scores ($M = 34.3$, $SD = 7.5$) compared to learners who were not studying for a HE qualification ($M = 33.0$, $SD = 7.3$); $t(786) = 2.069$, $p = .04$. There were significant differences in self-satisfaction and evaluation scores between learners studying for a HE qualification ($M = 18.1$, $SD = 3.9$) and learners who were not studying for a HE qualification ($M = 17.4$, $SD = 4.1$); $t(786) = 2.04$, $p = .03$. There also were significant differences in the task interest between learners studying for a HE qualification ($M = 13.0$, $SD = 2.0$) and learners who were not studying for a HE qualification ($M = 12.5$, $SD = 2.1$); $t(786) = 2.715$, $p = .01$. Learners studying for a HE qualification also had significantly higher learning challenge scores ($M = 22.7$, $SD = 4.3$) compared to learners who were not studying for a HE qualification ($M = 22.0$, $SD = 4.3$); $t(786) = 2.104$, $p = .04$.

The implications of these findings, and in particular the similarities and differences between the results for learners who were employed as data professionals and learners who were studying towards a HE qualification will be discussed in the following section.

6. Discussion

The data indicate that a learner's context and role not only influence their overall self-regulation in a MOOC but also are a significant predictor for how a learner will implement each specific SRL sub-process. Both learners employed as data

Table 4
Results of t-test and Descriptive Statistics for SRL scores for learners employed as data professionals and learners who were not employed as data professionals.

	Role/Context								
	Working as data professional			Not working as data professional					
	M	SD	n	M	SD	N	t	df	p
Overall SRL score	147.8	23.8	362	144.3	25.1	426	1.99	786	.05*
F.1 Goal setting	23.2	5.7	362	23.0	6.0	426	.50	786	.62
F.2 Self efficacy	31.4	5.0	362	30.0	5.6	426	3.75	786	.00**
F.3 Task strategies	34.0	7.3	362	32.8	7.5	426	2.15	786	.03*
F.4 Learning strategies	21.7	4.6	362	21.2	4.8	426	1.56	786	.12
F.5 Help seeking	10.1	4.1	362	10.1	4.2	426	–.19	786	.85
F.6 Self-satisfaction and evaluation	17.9	4.0	362	17.3	4.1	426	2.36	786	.02*
F.7 Task interest	12.7	2.1	362	12.6	2.2	426	1.19	786	.23
F.8 Learning Challenge	22.3	4.3	362	22.0	4.2	426	1.24	786	.22

$^{**}p < .001$ $^{*}p < .05$.

Table 5
Results of t-test and Descriptive Statistics for SRL scores for learners currently studying towards a HE qualification and learners who were not studying towards a HE qualification.

	Role/Context								
	Studying for HE qualification			Not studying for HE qualification					
	M	SD	n	M	SD	N	t	df	p
Overall SRL score	149.9	25.2	200	145.8	25.1	588	2.189	786	.03*
F.1 Goal setting	23.6	6.0	200	23.0	5.8	588	1.360	786	.17
F.2 Self efficacy	30.9	5.3	200	30.5	5.4	588	.714	786	.48
F.3 Task strategies	34.3	7.5	200	33.0	7.3	588	2.069	786	.04*
F.4 Learning strategies	22.0	4.9	200	21.3	4.7	588	1.813	786	.07
F.5 Help seeking	10.3	4.4	200	10.1	4.1	588	.712	786	.48
F.6 Self-satisfaction and evaluation	18.1	3.9	200	17.4	4.1	588	2.204	786	.03*
F.7 Task interest	13.0	2.0	200	12.5	2.1	588	2.715	786	.01*
F.8 Learning challenge	22.7	4.3	200	22.0	4.3	588	2.104	786	.04*

*$p < .05$.

professionals and learners who were studying toward a HE qualification had significantly higher overall SRL scores as well as higher scores for specific SRL sub-processes.

The most significant difference was identified in the self-efficacy scores between learners who were working as data science professionals and learners who were not. Self-efficacy is associated with the extent to which an individual learner feels confident in their ability to engage with and complete learning activities. The importance of contextualising learning may be associated with the higher average self-efficacy score for participants working as data professionals. Self-efficacy is context specific (Bandura, 2001) and therefore is prone to improve, partly as a result of experience. In this study, self-efficacy was associated with the extent to which an individual felt confident in their ability to engage with and complete the learning activities offered in the MOOC. The connection between the content of the MOOC (Introduction to Data Science) and the professional work of participants working as data professionals may have contributed to their higher self-efficacy scores.

The significantly higher average task strategy scores of data professionals, also suggests that familiarity with course content may further enable learners to identify and employ meaningful learning approaches and strategies. These learners' higher self-efficacy enables them to better plan and moderate their learning activity. Similarly to those participants working as data professionals, participants who were currently working towards a HE qualification also scored significantly higher for task strategies. They perceived that they were better able to plan and moderate their behaviour and actions to positively influence their learning. It is possible that the nature of the learning experience on a MOOC has parallels to the learning process they were engaged with for their HE qualification, supporting their ability to identify and employ strategies that will support them in their learning.

Participants employed as data professionals and those studying for a HE qualification also had significantly higher self-satisfaction and self-evaluation scores. Self-satisfaction and self-evaluation reflects how learners connect what they are learning with their own current context, assessing how their learning relates to their wider work or educational practice. These findings indicate that participants who were either current students or data professionals could more easily recognise the connections between the content and skills being addressed in the MOOC and their current or future contexts and needs. They also, importantly perceived that they were better able to evaluate their learning in relation to their own situation and setting.

Participants studying for a HE qualification also had significantly higher scores for task interest and learning challenge. Both task interest and learning challenge relate to an individual's intrinsic motivation to learn and their participation in learning for the internal sense of fulfilment it offers them. It is possible that their engagement in more formal-style learning for an HE qualification might influence their intrinsic motivation to engage in other learning opportunities. That data professionals did not score significantly higher in task interest and learning challenge could indicate that their motivation to participate in a MOOC is less intrinsically driven than HE students.

The higher overall SRL scores of both participants studying for a HE qualification and those working as data professionals is interesting given that the primary learning in each of those two contexts is different. Learning in HE contexts tends to incorporate more formal learning elements whereas much workplace learning is largely informal in nature (Eraut, 2004). The emergence of significantly higher scores in participants from both groups for two sub-processes – task strategy and self-satisfaction – suggests that both groups of participants were able to employ meaningful learning approaches and strategies in the MOOC. The higher self-efficacy scores for data professionals suggest that confidence to participate and learn in a MOOC may be connected to familiarity with the content of the MOOC. The higher task interest and learning challenge scores of students currently studying for a HE qualification indicate that engagement in other formal learning activities may raise intrinsic motivation in MOOC participants. Overall, these findings suggest that the context and current experience of a MOOC participant can influence their self-regulated learning behaviour. The statistical differences in the scores of particular sub-processes for different groups of learners suggests that both the other learning activities that participants are engaged with as well as the connection between their current roles and the topic of a MOOC may influence their learning behaviour.

7. Conclusions

This study provides empirical evidence that a learner's current context and role influences their learning in a MOOC. Learners who were working as data professionals and/or studying towards a HE qualification appeared more highly self-regulated, exhibiting significantly higher SRL scores than those learners who were not working as data professionals or studying for a HE qualification. The self-directed, non-linear nature of learning engagement in MOOCs, which requires individuals to determine and structure their learning largely independently, combined with the diverse range of learners MOOCs attract, makes this finding particularly meaningful.

The relationship between a learner's context and role and their ability to self-regulate their learning has important implications for the structure and operation of MOOCs. An individual's self-regulation of learning is not static but may vary depending on the learning context. MOOCs operate as non-formal learning activities (Gillani & Eynon, 2014; Gillani, Yasseri, Eynon, & Hjorth, 2014). Whilst incorporating elements of traditional, formal higher education, MOOCs also facilitate flexible learning, requiring individual participants to choose how, when and in what ways they engage. Connecting the learning occurring on MOOCs to 'real-world' contexts and the lives of learners could play an important role in supporting learning. The differences in overall perceived ability to self-regulate (measured though SRL scores) between learners from different contexts and roles, combined with the findings from previous studies suggesting the importance of SRL to achievement outcomes (Azevedo & Cromley, 2004; Barnard-Brak, Lan, & Paton, 2010), highlights the need for greater attention to be paid to how MOOCs can better support learners from all backgrounds.

As with any study there are a number constraints and limitations placed on both the design and the findings. The quantitative approach adopted by this study was intended to identify the relationship between a series of variables within a single context – learner's engagement in the Introduction to Data Science MOOC – and there is no attempt to generalise the findings beyond this specific setting. Conducting further studies, which investigate learners' backgrounds and their SRL behaviour in a variety of MOOCs would help in the development of a broader understanding of the relationship between learner backgrounds and contexts and their learning in a MOOC. Given that SRL behaviour varies depending on the context, tracking learners' self-regulated learning across a range of MOOCs or across various learning contexts (MOOCs, formal education, workplace learning) could enable deeper insight into the relationship between context and SRL.

The employment of qualitative studies could enrich the findings of this quantitative research by providing insight into the individual stories and experiences of learners. Qualitative methods would facilitate a more in-depth and nuanced examination of the relationship between self-regulation and work or study context, through exploring individual's learning behaviours in relation to their contexts and roles. Additionally, as previous research has determined that an individual's ability to self-regulate their learning does not remain static (Pintrich, 2000) but rather changes over time as their expertise evolves and they engage in new learning environments, it would be interesting to measure how an individual's SRL disposition changes as they engage in a range of learning contexts, including different MOOCs.

A challenge facing all studies of self-regulated learning, and in particular those focussing on online learning contexts, is trying to observe and measure the SRL sub-processes. The instrument employed in this study utilised self-report measures and therefore is reliant on individual learners to accurately assess their ability to self-regulate their learning. Self-report measures and the emphasis on individual perception have been employed widely in SRL research in both offline and online contexts and studies focussing on both formal and informal learning (Fontana et al., 2015; REFERENCE 6 REMOVED FOR BLIND REVIEW; Pintrich & de Groot, 1990; Zimmerman, 2001). They are accepted as providing an appropriate approach as long as the findings are understood to be relative to the particular setting and individuals, rather than absolute (Fontana et al., 2015). Expanding this study through the employment of qualitative methods would support the robustness of the findings.

Despite these limitations, the findings provide clear evidence for the relationship between a learner's context and role and their self-regulation of learning in a MOOC. Given the diversity of learners participating in MOOCs, who each bring different experience, education-backgrounds and skill levels and varied motivations for taking the MOOC, and the importance of learners being able to self-direct and individually determine their learning journey within a MOOC, this finding is particularly significant. By facilitating a deeper understanding of the SRL sub-processes most important for effective participation and learning in a MOOC as well as identifying the connection between SRL dispositions and learners' contexts, this study has important implications for MOOCs. The findings are particularly relevant to the ability of MOOCs to fulfil their potential of providing freely available, open access, high quality learning opportunities to all.

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