

The Open University's repository of research publications
and other research outputs

Learning in MOOCs: A Comparison Study, Proceedings of the European Stakeholder Summit on experiences and best practices in and around MOOCs

Conference or Workshop Item

How to cite:

Milligan, Colin; Littlejohn, Allison and Hood, Nina (2016). Learning in MOOCs: A Comparison Study, Proceedings of the European Stakeholder Summit on experiences and best practices in and around MOOCs. In: Proceedings of the EUROPEAN STAKEHOLDER SUMMIT on experiences and best practices in and around MOOCs (EMOOCs 2016) (Khalil, Mohammad; Ebner, Martin; Kopp, Michael; Lorenz, Anja and Kalz, Marco eds.), Karl-Franzens-Universität Graz, Graz, pp. 15–26.

For guidance on citations see [FAQs](#).

© 2016 The Authors



<https://creativecommons.org/licenses/by-nc-nd/4.0/>

Version: Version of Record

Link(s) to article on publisher's website:

<http://emoocs2016.eu/wp-content/uploads/2016/02/proceedings-emoocs2016.pdf>

Copyright and Moral Rights for the articles on this site are retained by the individual authors and/or other copyright owners. For more information on Open Research Online's data [policy](#) on reuse of materials please consult the policies page.

Learning in MOOCs: A Comparison Study

Colin MILLIGAN¹, Allison LITTLEJOHN² & Nina HOOD³

¹ Caledonian Academy, Glasgow Caledonian University, UK,
colin.milligan@gcu.ac.uk

² Institute for Educational Technology, The Open University, UK,
allison.littlejohn@open.ac.uk

³ Faculty of Education, University of Auckland, New Zealand,
n.hood@auckland.ac.nz

Abstract

Massive Open Online Courses (MOOCs) have emerged as a significant environment for online learning, yet little is known about how people actually learn in a MOOC. The study brings together qualitative data from parallel studies in two different MOOCs, comparing learning strategies of people who self-report low and high levels of Self-Regulated Learning (SRL). This comparative study identifies commonalities and differences in learning patterns between these two learner groups and across the two courses. The study draws comparisons in goal-setting, self efficacy, and the selection of learning and task strategies. The study concludes that differences in the learning strategies of learners in each of the MOOCs may be influenced by different course design.

Keywords

Self-regulated learning, SRL, self efficacy, help-seeking, task strategies

1 Introduction

A recent study of the instructional design quality of 75 Massive Open Online Courses (MOOCs) concluded that MOOCs from major providers are generally of low instructional quality (MARGARYAN, BIANCO & LITTLEJOHN, 2015). These MOOCs are typically designed around the presentation of content resources to large numbers of learners. Learners have few programmed opportunities to engage in dialogue and receive feedback from instructors. This instructional design demands that learners self-regulate their learning, proactively seeking feedback from others and self-evaluating their progress to complement the learning content. Yet, MOOCs attract diverse groups of learners, many of whom may lack the ability to self-regulate, or choose not to regulate their own learning (MILLIGAN, LITTLEJOHN & MARGARYAN, 2013). This presents a design challenge to MOOC providers: to create MOOC environments that encourage and assist learners to self-regulate their learning. MOOCs are still novel, and we know very little about how individuals learn in MOOCs. Research in this domain is vital in developing our understanding of how to design MOOC environments that encourage active agency in learning. In this paper we compare the findings of two parallel studies of self-regulated learning (SRL) in MOOCs aimed at professionals (data scientists and those conducting clinical trials), exploring the commonalities and differences that emerge from this analysis. Each study used the same qualitative and quantitative instruments to explore individual self-regulation of learning (ZIMMERMAN, 2000). The paper begins with a short review of current research on MOOCs. This review is followed by a description of the method and context of the two courses under study, and the instruments used. The results are then presented and discussed. The paper concludes with a summary of the main findings and implications, alongside a reflection on the limitations of the study and prospects for future research.

2 Literature Review

While initial MOOC research was often qualitative, quantitative studies have become dominant with the emergence of large scale MOOC platforms that permit the generation and analysis ‘clickstream’ data (VELETSIANOS, COLLIER & SCHNEIDER, 2015). Attempts to interpret clickstream data include mining the data tracking how

learners access MOOC resources and classifying learners according to their patterns of interaction with content (KIZILCEC, PIECH & SCHNEIDER, 2013) or with other learners in online discussion forums (GILLANI & EYNON, 2014). These studies have demonstrated links between engagement and completion (where completion is used as measure of learning success). But while these quantitative studies of learner activity within MOOC platforms provide us with greater understanding of *what* learners do within MOOCs, our understanding of *why* MOOC participants learn as they do, and *how* they actually learn is less developed (VELETSIANOS COLLIER & SCHNEIDER, 2015, p571). Furthermore, unlike in traditional HE courses where learner expectations are largely standardised (for example successful completion of a course or degree programme as a marker of success), the diversity of learners in a MOOC results in a range of motivations for participation (KIZILCEC PIECH & SCHNEIDER, 2013) and potentially leads to different levels of engagement (BRESLOW, PRITCHARD, DEBOER, STUMP, HO & SEATON, 2013) which may not be focused on completion. To understand learning in MOOCs it is necessary to move beyond the artificial binary distinction between completers, and non-completers, to more fully investigate the particular motivations and drivers, including contextual, cognitive, and behavioural factors, that influence individual learners’ behaviour and actions. GAŠEVIĆ, KOVANOVIĆ, JOKSIMOVIĆ & SIEMENS (2014, p. 168) call for studies that improve our understanding of ‘motivation, metacognitive skills, learning strategies and attitudes’ 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. Self-regulation is the ‘self-generated thoughts, feelings and actions that are planned and cyclically adapted to the attainment of personal goals’ through three phases: forethought, performance, and self-reflection (ZIMMERMAN, 2000, p. 14). Zimmerman identified a number of components (sub-processes) of self-regulation including goal-setting, self-efficacy, learning and task strategies, and help-seeking. Although originally conceptualised in formal (classroom) settings, SRL and its sub-processes have subsequently been studied extensively in online contexts (see BERNACKI, AGUILAR & BYRNES, 2011 for a comprehensive review) and SRL is increasingly being used to investigate learning in MOOCs.

ZIMMERMAN (2000) highlights goal-setting as a central component of SRL. By setting goals, the learner is able to monitor progress towards those goals, adjusting their

learning as necessary. Setting goals and monitoring them is motivational as it provides evidence of progress to the learner. HAUG, WODZICKI, CRESS & MOSKALIUK (2014) explored the utility of badges in a MOOC focused on emerging educational technologies. The authors used self-report questionnaires and log files to explore patterns of participation, and found that learners who had set a goal to complete the course were more likely to sustain their participation (determined by measuring access to course content and active engagement with others about the course) than those who did not set a goal. Completion of the course provided an extrinsic motivation for these learners (RYAN & DECI, 2000). However, as highlighted above, MOOC learners may not be motivated by completion, so it is important to understand different types of motivation for studying in MOOCs. ZHENG, ROSSON, SHIH & CARROLL (2015) conducted interviews with learners who had undertaken a variety of MOOCs and identified four categories of MOOC learner motivation: fulfilling current needs, preparing for the future, satisfying curiosity, and connecting with people. Their findings suggest that completion is just one outcome of MOOC participation, with key motivations to study being intrinsic in nature, related to personal improvement. In a larger, survey based study, exploring motivations of MOOC learners based in the United Kingdom, Spain and Syria, seven different types of motivation were identified (WHITE, DAVIS, DICKENS, LEON & SANCHEZ-VERA, 2015), mirroring the categories identified by the Zheng study, and in addition identifying categories of motivation reflecting other extrinsic factors: the free and open nature of MOOCs, their convenience, and the prestige of courses run by high quality institutions. These studies help to describe the types of goals learners may be setting, but do not tell us about how different types of goals influence learning in MOOCs.

Self-efficacy, the personal belief about having the means to perform effectively in a given situation (BANDURA, 1986), represents another component of self-regulation. An individual's self-efficacy influences how they respond to setbacks in their learning, with highly self-efficacious individuals redoubling their efforts in an attempt to meet their goals when faced with a challenge, while those lacking self-efficacy may give up or become negative (ZIMMERMAN, 2000). In a study of learners registered for a MOOC on economics, POELLHUBER, ROY, BOUCHOUCHA & ANDERSON (2014) explored the relation between self-efficacy and persistence using clickstream data and scales for self-efficacy and self-regulation. Their study found a positive link

between self-efficacy and persistence, though the main predictor they identified was initial engagement. WANG & BAKER (2015) studied participants on a Coursera MOOC on big data in education to explore the link between motivation, self-efficacy and completion. They found that participants who self-reported higher levels of self-efficacy at the outset of the course were more likely to persist to the end, echoing findings from online learning research (WANG & NEWLIN, 2002).

Learners draw on a range of cognitive and metacognitive strategies (learning and task strategies) to support their learning, including taking notes, revising, supplementing core learning materials, exercising time management and undertaking ongoing planning and monitoring. Highly self-regulated learners draw on a wider range of strategies and recognise the applicability of different strategies to different situations (ZIMMERMAN, 2000). They are also able to effectively monitor their learning, changing strategies when they become ineffective. VELETSIANOS COLLIER & SCHNEIDER, (2015) explored the learning strategies of a small group of learners who had completed at least one MOOC, focusing on note-taking and content consumption. Their interviews uncovered a range of different note-taking strategies that facilitated these individuals' engagement with the course content. The range of note-taking strategies utilised illustrated how different approaches such as taking digital notes, using a dedicated notebook, or annotating printed slides, complemented different patterns of participation and engagement.

3 Context and Method

The study draws on data collected in studies of SRL in two separate MOOCs. Both MOOCs attracted participants who were professionals wishing to update or supplement their professional skills or to gain a certificate in the topic as evidence of their knowledge. The *Introduction to Data Science* MOOC (IDS: <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 included four programming

assignments. 50,000 learners, from 197 countries enrolled in the MOOC. A full method and findings of this study are reported elsewhere (LITTLEJOHN, HOOD, MILLIGAN & MUSTAIN, forthcoming). The *Fundamentals of Clinical Trials* MOOC (FCT: <https://www.edX.org/course/harvard-university/hsph-hms214x/fundamentals-clinical-trials/941>) provided an introduction to the research designs, statistical approaches, and ethical considerations of clinical trials. The course was aimed at health professionals and those studying for a health professional role. The course used video lectures, multiple choice questions and weekly readings and participants were invited to contribute to two moderated case discussions if they wished to gain a completion certificate. The course attracted 22,000 registrants from 168 countries. Full details of the method and findings of this study are reported separately (MILLIGAN & LITTLEJOHN, forthcoming). In both studies the participants were drawn from a larger cohort of learners who responded to a message posted to the course environment in the first weeks of the course inviting them to fill in a slightly revised version of a previously validated survey instrument (FONTANA, MILLIGAN, LITTLEJOHN & MARGARYAN, 2014; <http://dx.doi.org/10.6084/m9.figshare.866774>). The instrument comprised 39 items (example: When I do not understand something, I ask others for help.), used a Likert-scale (ranging from 1: not at all true for me to 5: very true for me). The data collected was used to generate an SRL profile for each study participant comprising an overall SRL score, as well as scores for each of eight SRL sub-processes corresponding to factors identified following principal component analysis. The SRL profile provides an indication of the extent to which individuals are regulating their learning within the MOOC. Participants who completed the survey instrument, and who identified as professionals, were invited for interview to explore their learning within the MOOC. A semi-structured interview instrument (<http://dx.doi.org/10.6084/m9.figshare.1300050>), developed iteratively over a number of studies (MILLIGAN, LITTLEJOHN & MARGARYAN, 2013; LITTLEJOHN, MILLIGAN, FONTANA & MARGARYAN, forthcoming) was used to probe SRL sub-processes. Transcripts were analysed and narrative descriptions of learning in the MOOC were coded according to these sub-processes. For the *Introduction to Data Science* course, thirty-two Skype interviews were conducted. For the *Fundamentals of Clinical Trials* course, thirty-five Skype interviews were conducted. Qualitative data was integrated with quantitative data using a three step method. First interview transcripts were coded independently by two re-

searchers. Second, each participant was assigned a rank corresponding to their score for each individual SRL sub-process as well as a rank for their overall SRL score, and assigned into high- and low-scoring groups for their overall and sub-process scores. Third, the coded transcripts were examined by two researchers (independently, then jointly, to reduce the risk of bias) to identify emergent patterns of learning in the low and high-scoring groups.

4 Results

For the analysis reported in this paper, the findings of the two parallel studies were compared and commonalities and differences identified. The summaries below focus on individual aspects of SRL, reflecting the initial coding of the interviews. Narrative accounts of learning in MOOCs focused on a sub-set of SRL sub-processes and in particular, three aspects of SRL stood out: *goal-setting*, *self-efficacy*, and *learning and task strategies*.

4.1 Goal-setting

High self-regulators in both studies set specific goals highlighting the benefits of their learning, and how it related to career or job requirements. These learners were adopting a ‘mastery goal orientation’, setting specific goals relating to the course content and how it related to their professional needs, and structuring their learning around the development of content knowledge and expertise (PINTRICH, 1999). In contrast, low self-regulators described their learning in more abstract terms, focusing on their love of learning, curiosity, or desire to broaden their knowledge. If they articulated specific goals, they were focused solely on extrinsic performance measures such as course completion or certification, in contrast to the targeted goals favoured by the high self-regulators. The range of goals set reflects the range of motivations (both intrinsic and extrinsic) identified by ZHENG, ROSSON, SHIH & CARROLL (2015) and by WHITE, DAVIS, DICKENS, LEON & SANCHEZ-VERA (2015). In the *Fundamentals of Clinical Trials* course (but not the *Introduction to Data Science* course), there is evidence of high self-regulators adopting performance goals (to complete the course or gain a certificate) in addition to learning focused goals. Two differences between the

courses may account for this discrepancy. First, the FCT course was offered by Harvard Medical School, and many participants highlighted the prestige of Harvard in the goals they described, stating their desire to complete a Harvard course, or ‘learn from the best’. This sentiment reflects one of the key motivations identified by WHITE, DAVIS, DICKENS, LEON & SANCHEZ-VERA (2015). Second, the FCT course had a more rigid structure that encouraged all participants, whether low- or high-self-regulators to become wholly focused on the course content and objectives. Perhaps because of this, high self-regulators on the FCT course were more likely to articulate goals that mirrored the course objectives than the IDS course participants.

4.2 Self-efficacy

Across both studies, there was evidence of high self-efficacy among most participants, with little difference between the low and high SRL groups. The lack of a clear-cut difference is perhaps unsurprising, as the participants in this study are highly-educated, experienced professionals and are, therefore, expected to be confident in their ability to extend their existing knowledge and expertise. Furthermore, the sampling approach used in these studies (recruiting participants active some weeks into the course) is likely to favour those whose self-efficacy helped them to persist with their learning. Self-efficacy, like many aspects of SRL, is highly context dependent, and one factor which seemed to influence self-efficacy across both studies was previous experience of MOOC learning. MOOCs still represent a novel way to learn and the format can present a challenge for even the most able learners if they have not encountered them before. Indeed, learning online in any form can challenge an individual’s confidence. CHANG (2005) demonstrated how training in a range of self-regulatory strategies led to improved self-efficacy in an online context. MOOC designers may consider providing some initial orientation training to ensure that learners are familiar with the course environment and how they may interact effectively with it.

4.3 Learning and Task Strategies

Whereas high self-regulators in each course generally behaved in a similar fashion, this was not the case for learning and task strategies. In the *Fundamentals of Clinical Trials*

MOOC, all high self-regulators used note-taking as a key strategy, with the majority of this same group maintaining the same approach to learning throughout the course. In contrast, the high self-regulators studying on the *Introduction to Data Science* Course displayed a wide variation in the learning strategies adopted, with this group being more flexible in their approach to learning, adapting their approach to suit different elements of the course. Once again, the differences appear linked to the different course structures adopted. For the FCT course, almost every week followed the same format, with video lectures, course readings and closely linked self-assessment quizzes inviting a standard learning approach of watching, reading, and answering, and a simple note-taking approach was sufficient. In contrast, the IDS course made extensive use of project work, where learners were invited to complete an exercise in data manipulation. These in depth tasks encouraged learners to focus their learning on those aspects which were of most relevance to them and to use a broader range of strategies to meet the demands of the course.

5 Conclusion

The analysis presented here helps us to recognize learning exhibited by MOOC learners across the two study contexts. Regardless, of context, high self-regulators will focus their effort on learning: extending their knowledge and expertise to benefit their current or future roles. This is the case regardless of whether they were intending to complete the course, or study more strategically. In contrast, low-self regulators focus primarily on performance, aiming to complete the course, with less (conscious) regard for what they want to learn. At least among the professionals studying here, there was a high level of confidence in their ability to learn, though this was sometimes diminished if the individual was an inexperienced MOOC learner. But context is also important. The rigid structure of the *Fundamentals of Clinical Trials* course encouraged learners to fall into line, all progressing through the course in a similar fashion. In contrast, the more in-depth tasks that formed the core of the *Introduction to Data Science* Course encouraged learners to focus their learning on those aspects which were of most relevance to them.

While this study has begun to address a key limitation of single context qualitative studies, this analysis is not without its limitations. Only two courses were studied, and many more contexts would need to be examined before clear patterns can be recognized. Even so, qualitative analysis on its own is unable to provide a reliable measure of the similarities and differences of MOOC learners. Integrating qualitative analyses such as the ones reported here with clickstream data such as forum use, content access, and final mark would allow more robust conclusions to be drawn with rich descriptions of learning illuminating the quantitative analysis. Nevertheless, the power of this analysis in highlighting commonalities and differences has provided insight into potential areas for future exploration and signals the dual importance of learner characteristics and context in MOOC learning. Course and platform designers may use the instruments developed in this study and the findings presented here to assist them in designing courses that support inexperienced learners, whilst motivating more able ones (LITTLEJOHN & MILLIGAN, 2015). For example, course designs that encourage learners to adopt a more active role in their learning by requiring them to utilise their own expertise or integrate learning into their work contexts may be particularly appropriate for professional learners who typically have focused learning requirements.

References

Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory*. Englewood Cliffs, NJ: Prentice Hall.

Bernacki, M. L., Aguilar, A., & Byrnes, J. (2011). Self-regulated learning and technology-enhanced learning environments: An opportunity propensity analysis. In G. Dettori and D. Persico (Eds.), *Fostering self-regulated learning through ICT* (pp. 1-26). Hershey, PA: IGI Global Publishers.

Breslow, L., Pritchard, D. E., DeBoer, J., Stump, G. S., Ho, A. D., & Seaton, D. T. (2013). Studying learning in the worldwide classroom: Research into edX's first MOOC. *Journal of Research & Practice in Assessment*, 8, 13-25.

Chang, M. M. (2005). Applying self-regulated learning strategies in a web-based instruction – an investigation of motivation perception. *Computer Assisted Language Learning*, 18(3), 217-230.

Fontana, R. P., Milligan, C., Littlejohn, A., & Margaryan, A. (2015). Measuring self-regulated learning in the workplace. *International Journal of Training and Development*, 19(1), 32-52.

Gašević, D., Kovanović, V., Joksimović, S., & Siemens, G. (2014). Where is Research on Massive Open Online Courses Headed? A Data Analysis of the MOOC Research Initiative. *International Review of Research in Open and Distance Learning*, 15(5), 134-176.

Gillani, N., & Eynon, R. (2014). Communication patterns in massively open online courses. *The Internet and Higher Education*, 23, 18-26.

Haug, S., Wodzicki, K., Cress, U., & Moskaliuk, J. (2014). Self-Regulated Learning in MOOCs: Do Open Badges and Certificates of Attendance Motivate Learners to Invest More? In U. Cress & C. D. Kloos (Eds.), *EMOOCs 2014 – European MOOC Stakeholder Summit* (pp. 66-72). Lausanne, Switzerland.

Kizilcec, R. F., Piech, C., & Schneider, E. (2013). Deconstructing disengagement: Analyzing learner subpopulations in massive open online courses. In *Proceedings of the 3rd International Conference on Learning Analytics and Knowledge* (pp. 170-179). New York, NY, USA: ACM. Retrieved April 8, 2015, from <http://dl.acm.org/citation.cfm?id=2460330>

Littlejohn, A., & Milligan, C. (2015). Designing MOOCs for professional learners: tools and patterns to encourage self-regulated learning. *eLearning Papers*, 42, 38-45.

Littlejohn, A., Hood, N., Milligan, C., & Mustain, P. (accepted). Learning in MOOCs, motivations and self-regulated learning. *The Internet and Higher Education*.

Littlejohn, A., Milligan, C. Fontana, R. P., & Margaryan, A. (accepted). Professional learning through everyday work: how finance professionals self-regulate their learning. *Vocations and Learning*.

Margaryan, A., Bianco, M., & Littlejohn, A. (2015). Instructional quality of Massive Open Online Courses (MOOCs). *Computers & Education*, 80, 77-83.

Milligan, C., Littlejohn, A., & Margaryan, A. (2013). Patterns of engagement in connectivist MOOCs. *Journal of Online Learning & Teaching*, 9(2), 149-159.

Milligan, C., & Littlejohn, A. (2014). Supporting professional learning in a massive open online course. *International Review of Research in Open and Distance Learning*, 15(5), 197-213.

Milligan, C., & Littlejohn, A. (under review). How health professionals regulate their learning in MOOCs.

Pintrich, P. R. (1999). The role of motivation in promoting and sustaining self-regulated learning. *International Journal of Educational Research*, 31, 459-470.

Poellhuber, B., Roy, N. Bouchoucha, I., & Anderson, T. (2014). *The relationships between the motivational profiles, engagement profiles and persistence of MOOC participants*. MOOC Research Initiative, Final Report.

Ryan, R. M., & Deci, E. L. (2000). Intrinsic and extrinsic motivations: classic definitions and new directions. *Contemporary Educational Psychology*, 25, 54-67.

Veletsianos, G., Collier, A., & Schneider, E. (2015). Digging Deeper into Learners Experiences in MOOCs: Participation in social networks outside of MOOCs, Notetaking, and contexts surrounding content consumption. *British Journal of Educational Technology*, 46, 570-587.

Wang, A. Y., & Newlin, M. H. (2002). Predictors of web-student performance: The role of self-efficacy and reasons for taking an on-line class. *Computers in Human Behavior*, 18, 151-163.

Wang, Y., & Baker, R. (2015). Content or platform: why do students complete MOOCs. *MERLOT Journal of Online Learning and Teaching*, 11(1), 17-30.

White, S., Davis, H., Dickens, K. P., Leon, M., & Sanchez Vera, M. (2015). MOOCs: What motivates producers and participants. In S. Zvacek, M. Restivo, J. Uhomoihi, & M. Helfert (Eds.), *Proceedings of the 6th International Conference on Computer Supported Education* (pp. 99-114). Heidelberg: Springer.

Zheng, S., Rosson, M. B., Shih, P. C., & Carroll, J. M. (2015). Understanding Student Motivation, Behaviors and Perceptions in MOOCs. In *Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing* (pp. 1882-1895). ACM.

Zimmerman, B. J. (2000). Attaining self-regulation: a social cognitive perspective. In M. Boekaerts, M. Zeidner, & P.R. Pintrich (Eds.), *Handbook of self-regulation* (pp. 13-39). San Diego, CA: Academic Press.

Exploring learning objectives at scale through concept mapping of MOOC learner discussions

Silvia Elena GALLAGHER & Timothy SAVAGE

Trinity College Dublin, The University of Dublin, College Green, Dublin 2, Ireland, {sgallag1, tsavage}@tcd.ie

Abstract

Evaluating whether MOOC learners are aligning with learning objectives is often difficult to understand at scale. This paper explores whether concept mapping through text mining software can help MOOC providers assess whether learners are meeting the learning objectives of the MOOC. 67,557 learner comments from the Trinity College/Futurelearn 'Irish Lives' History MOOC were analysed using Leximancer software, and concept maps based on data extracted were created. These maps were then aligned with pre-defined learning objectives to determine whether this software could be used to better understand learner behavior in relation to MOOC learner objectives. This research, through observation of the learning process, contributes a new methodology for understanding learning objectives in MOOCs at scale.

Keywords

Massive Online Open Courses, MOOCs, Learning Objectives, Leximancer, Text Mining, Concept Mapping