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Connecting performance to social structure and pedagogy as a pathway to scaling learning analytics in MOOCs: an exploratory study

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Abstract This exploratory study focuses on the design and evaluation of teaching analytics that relate social learning structure with performance measures in a massive open online course (MOOC) prototype environment. Using reflexive analysis of online learning trace data and qualitative performance measures we present an exploratory empirical study that: (a) rigorously evaluates a novel, multi-dimensional performance construct; (b) describes differences in small group dynamics and structure; and (c) draws a connection between learning performance and group structure. Performance is operationalized using a combination of knowledge construction measurement from discussion boards, rigorous analysis of student work products and several indicators of small group identity in the course examined. Interview and observational data are used to develop an approach for deriving and validating a model of the social structure of students in the course using traces of interaction data. The connection between performance and structure is developed at the small group unit of analysis. Implications for MOOC design, scaling MOOC analytics and a vision for developing social sensors in MOOC environments are presented in the discussion and conclusion.

Keywords learning analytics, MOOC, network analysis, small group, social sensors, virtual learning environments.

Introduction

Massive open online courses (MOOCs) hold the potential to meet growing demand for support of learning in an increasingly distributed and resource-constrained world. MOOCs also hold potential as sites for exploration of new approaches to online learning. In many respects, MOOCs are an ideal context for developing and refining online teaching techniques and learning analytics – particularly those that aid teachers in the early identification of students and groups likely to perform poorly or fail to complete a course. MOOCs are intriguing as a vehicle for scaling curriculum and gaining efficiencies in course execution. Practice across a range of disciplines suggests, however, that building a massive social computing system of any type begins with smaller scale prototypes. (Tapia, Bajpai, Jansen, Yen, & Giles, 2011; Xing, Chen, Chen, Wadholm, & Goggins, 2014). In the specific case of analytics for MOOCs, exploratory studies on a smaller scale enable the recovery of more nuanced and reliable signals from the noise of trace data generated by massive online systems (Graves, McDonald, & Goggins, 2014).

There are many different, specific instantiations of 'MOOCs', with a high degree of technological and pedagogical variation. MOOC Analytics research, broadly envisioned across this heterogeneous landscape, begins with a premise that learning itself is already being

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executed 'at scale' through MOOCs and there is a need for analytic methods that can scale up accordingly. There are several, general paths to support such MOOC analytics scalability, including educational data mining (Baker & Yacef, 2009; Reimann, Frerejean, & Thompson, 2009; Romero & Ventura, 2007, 2010; Xing & Goggins, 2014), multivocal methods that incorporate perspectives from a range of intellectual traditions in MOOC research (Goggins & Dyke, 2013; Suthers, Lund, Teplovs, Law, & Dyke, 2013) and Group Informatics, which takes a reflexive approach to making sense of trace data that combines ethnographic and data mining intellectual traditions (Goggins, Mascaro, & Valetto, 2013; Goggins & Petakovic, 2014; Goggins, Valetto, Mascaro, & Blincoe, 2013).

A principal issue for MOOC scalability in general, however, is the student dropout rate, and analytics (Yang, Sinha, Adamson, & Rosé, 2013). Scalability of MOOCs and Scalability of MOOC analytics are challenges that motivate not only technical analytical solutions, but also pedagogical ones. MOOCs are highly decentralized forms of technology mediated organization, which are demonstrated to scale well through highly centralized cores who support emergent, small working groups (Crowston & Howison, 2005; Mascaro & Goggins, 2011). A good deal of CSCL research also focuses on social theories of learning operationalized through small group pedagogical design (Sinha, 2014a, 2014b) and the performance measure benefits of a higher sense of social presence in small groups in online learning (Kreijns, Kirschner, Jochems, & Van Buuren, 2004). The notion of analytics aimed at small groups also extends on previous research examining learning in CSCL environments, and the support of robust online course discussion (De Groot et al., 2007).

Small group work scales pedagogically (Goggins, Laffey, & Amelung, 2011), and deep insights could inspire both more precise and scalable MOOC analytics not discoverable from computation alone. For example, analysis and visualization of the interactions among group members in an online system can reveal how small groups (three to five students) construct knowledge (Stahl, 2006). Because small group work is a viable pedagogical approach for scaling MOOCs and increases participant completion (Sinha, 2014b), in-depth examinations of asynchronous group work in environments similar to, but initially smaller than MOOCs could generate insight difficult to discern from a massive environment. Sinha (2014a, 2014b) identifies strategies for connecting group formation oriented social network analysis (SNA) (for example, identifying the most central members and members who broker information between groups) with psychological measures of individual capacity for learning. The work is promising, and a next step may be to evaluate knowledge construction or other performance measures like group identity (Arrow, McGrath, & Berdahl, 2000) against the emergent structures. Indeed, this is a difficult problem to solve.

Airoldi, Blei, Fienberg, and Xing (2008) also connect to psychosocial measures of capacity, but present analytical strategies in a context of affiliation networks in a *physically* situated classroom. There are gaps in our understanding of the link between analytics and pedagogy. For example, which specific approaches to the integration of qualitative and network analytic research methods will produce useful information for teachers in MOOCs? Network analytics approaches are promising, especially if combined with systematic, efficient qualitative research methods, but researchers and practitioners must be explicit about what they hypothesize social network connections to mean. Those hypotheses must then be verified, resulting in a context specific, network analytic ontology for learning analytics (Goggins et al., 2013).

What, for example, are the constructs and indicators most important for learning analytics to represent? Learning Analytics that use network analytic methods should be clear regarding the distinction between friend networks (2008), which is a record of who *knows* whom, and participation networks, which are a record of who *interacts* with whom and in what way (Goggins & Petakovic, 2014). If learning analytics examine trace data, the question of the importance of understanding student read behaviour through analysis of trace data may also be critical to the development of meaningful learning analytics (Goggins, Galyen, & Laffey, 2010; Wise, Hsiao, Marbouti, Speer, & Perera, 2012).

Envisioning scalable learning analytics that are appropriate for social learning contexts, we argue, requires reflexive analysis of small group interaction patterns, social structure and learning performance. Such triangulation is complex, and prior research shows such complexity is more productively prototyped in small group learning environments (Goggins, Laffey, & Gallagher, 2011; Stahl, 2006). Thus, this study explores the potential to achieve scalable MOOC analytics through a methodologically diverse approach focused on small, collaborative learning groups in 'small-scale' online courses. Current gaps in learning analytics research can be closed by studies that integrate qualitative measures of performance and network analytic indicators of group structure. Using qualitative methods to examine recognized small group performance measures like group identity and knowledge construction should enhance the utility of network analytic methods for learning analytics in MOOCs (Goggins et al., 2011). On a small scale, the integration of these two approaches as described in this article represent an incremental, exploratory step toward scalable MOOC analytics. Such approaches can lead to a more cooperative integration of pedagogy and analysis of group structure by providing MOOC *teachers* who integrate social learning into their instruction with a more informed understanding of what is occurring in their classes, and how student activities are connected to learning.

The aim of this exploratory study is to build an understanding of the types of analytics that could help *teachers* in MOOCs intervene and work with student groups by making more informed decisions regarding which groups need help, and which do not. In doing this, we focus on three specific research questions:

1. What social network structures are formed within online small groups and across online small groups during completely online group work?
2. How and to what extent do learning performance and group identity differ among small groups involved in a completely online course?
3. How and to what extent do performance indicators in completely online groups correspond with small group structure (social networks)?

Addressing these research questions will help in the development of more informed and focused teacher intervention in MOOCs and the grounding of computational analytics in: (a) findings derived from qualitative analysis of performance (learning and group identity) in one particular learning context and (b) fully developing the contextual information captured by the system logs in order to support analytics that reflect critical student actions related to learning. With the rest of this article we will review salient literature; describe the study context; present our findings and discuss the implications for the design of MOOC analytics. The result is a novel, exploratory path toward scaling learning analytics in MOOCs through comprehensive research on teaching analytics in small-scale environments.

Literature review

Teaching analytics and MOOCs

Potential of teaching analytics as a class of learning analytics

MOOCs exist at the intersection of open online communities and decades-old, smaller scale learning management systems. Open online communities literature examines the uptake and massive use of collaborative technologies for social engagement (Ellison, Steinfield, & Lampe, 2007; Lampe, Ellison, & Steinfield, 2006, 2008; Lampe et al., 2010), information management (Bryant, Forte, & Bruckman, 2005; Kittur & Kraut, 2008; Priedhorsky et al., 2007), open source software development (Crowston, Wiggins, & Howison, 2010; Crowston et al. 2012; Howison, Wiggins, & Crowston, 2012; Howison & Crowston, 2014) and a myriad of other purposes. Prior work in technology-mediated learning examines many different configurations of pedagogy and technology. Learning analytics are a kind of awareness research (Carroll, Rosson, Convertino, & Ganoe, 2006; Carroll, Rosson, Farooq, & Xiao, 2009) in socio-technical systems. However, in the case of a learning environment, where the goals are both time bound and well defined, awareness is too broad a construct; a narrower focus is needed. We want to not only be aware of others, but also of subtle social structures that may provide clues regarding the relationship between structure and performance. Analytics that support teachers – teaching analytics – and small group pedagogy will most likely contribute to improvements in teacher 'dynamic diagnostic decision-making' (Vatrapu, Teplovs, Fujita, & Bull, 2011, p. 93).

Reynolds and Goggins (2013) have shown that teaching analytics aid teachers in the identification of students at risk of performing at a lower level than the mean in asynchronous online environments. Xing and colleagues (Xing, Chen et al., 2014; Xing & Goggins, 2014; Xing, Wadholm, & Goggins, 2014, 2015) demonstrate similar, positive impacts for teachers in synchronous, math learning environments. A host of prior work suggests a reasonable path toward scaling learning analytics for MOOCs will include first providing useful teaching analytics (Vatrapu, Reimann, & Hussain, 2012).

The validity and utility gaps for learning analytics – those potentially addressed through focus on small groups and smaller scale evaluation – are secondary questions for scaling learning analytics more broadly. Specifically, Lonn, Aguilar, and Teasley (2013) observe that fundamental issues of infrastructure and collaboration with centralized campus information technology resource management are significant impediments to scalability. Questions of compatibility, support requirements, privacy and security are primary obstacles to scalability. Focusing first on teaching analytics has several advantages along these lines. Teachers already have access to student information, are fewer in number and therefore less time-consuming to support, and are less likely to misinterpret analytics than students. Teaching analytics, therefore, is a thread in the broader examination of learning analytics with significant potential for addressing institutional and 'usefulness' obstacles to scaling learning analytics.

Helping teachers foster collaboration among small groups is one potential strategy for teaching analytics research. Kumar, Gress, Hadwin, and Winne (2010) built a tool to inspect group knowledge construction and cognition using an ontological approach. They attempted to consider the full mode of collaborative activities that relate to group learning. The central question is, 'How does one go about designing a system that affords multiple collaborative opportunities while capturing all learner activities and the full context of their learning environments (e.g., open documents, notes being made, searches, conversations, and sharing) all on a standardized underlying metric?' They built their own ontologies to assess those aspects based on electronic trace data. Similarly, Milrad (2002) employed construction kits, modelling tools and system dynamics simulations to inquire into collaborative discovery learning. All the collaborative activities were recorded and transcribed so as to assess students' skills and knowledge acquisition. Building on this work, teaching analytics could benefit from better understanding of what kinds of signals correspond with differences in small group performance.

MOOC scalability issues

The literature notes that one of the keys to scaling learning in MOOCs is enhancing collaboration (Martin, 2012); and small group research broadly construed (Arrow et al., 2000; Brewer & Klein, 2006; Hardin, Fuller, & Davison, 2007; Hardin, Fuller, & Valacich, 2006; Katz, Lazer, Arrow, & Contractor, 2004; McGrath, 1991, 1997; Whittaker, 1996), as well as small group research focused on learning (Cakir, 2007; Goggins et al., 2011; Gross, Stary, & Totter, 2005; Howley, Mayfield, & Rosé, 2012; Michinov & Michinov, 2008), illustrates a myriad of cases in which collaboration is enhanced through deliberately structured small group work. Therefore, we argue that designing socio-technical learning systems to support effective small group learning is one way to scale online learning for MOOCs (Goggins et al., 2011).

The functions of a *small group* (three to six individuals) are to meet member needs, to maintain the group and to accomplish group goals (McGrath, 1991). We argue that a small group should be evaluated by more than just frequency counts of visible interactions among group members, which is a common mechanism by which online teachers currently evaluate students (Goggins & Foster, 2011). Systematic evaluation of who interacts with whom, how often (the structure of interaction), about what and in what way (the individual and group qualitative indicators of performance) will show greater utility than counting alone. It is only by understanding both of these halves (structure of interaction and indicators of performance) that a teacher may successfully employ teaching analytics to make sound, pedagogically based interventions. A comprehensive study of completely online small groups which takes a reflexive interpretation of structure and performance into account is an important step required to support the design and development of MOOCs as well as designing and then scaling teaching analytics.

Network analysis in online learning environments: interaction sequences

Network theory provides a particularly helpful frame for understanding the relationships between individuals and groups as they develop. This type of analysis holds great potential for the study of online collaborative groups, particularly where online activity logs are available. Unlike network analysis of physically situated groups, which has been criticized for relying on data with low reliability, use logs kept for online groups may be analysed using a computer record of their activities which can be reliably recorded and holds specific meanings. Network theory rests on five core positions (Katz et al., 2004):

1 Behaviour is best predicted by examining the relations people find themselves embedded in
2 The focus of analysis should be the relationships between units in a group
3 Analytical methods must assume that there is interdependence among individuals in a network, so normal assumptions of independence are not valid
4 Understanding a social system requires analysis of the structure of an entire network, not simply the ties between two members (dyadic ties)
5 Group relations are fuzzy, which means that where a specific group's boundaries are, and whether a particular individual is a member of a particular group is not clear-cut. Group assignment requires some judgement on the part of the researcher. Fortunately, there is ample prior work available to guide such judgements.

SNA is the method researchers use to guide empirical works framed by network theory. SNA has numerous specific forms, each informed to different degrees by graph theory, probability theory and algebraic modelling. The essential concepts represented by SNA are the *actor* – who can be an individual, group or event, the *relational tie* (between actors), *dyads* (two people), *triads* (three people), *groups*, *subgroups* and *networks*. Each actor is represented by a *node*, or a point, with each interaction or connection represented by a *tie* (or 'edge', depicted as a line between the two nodes). Next, we will briefly review the core concepts used in SNA, describe the small number of studies which have used SNA to describe online group development and review more computationally focused work that addresses the analysis of communication patterns and social networks using a myriad of online network data types.

Socio-centric density in a valued network describes the total of all actual connections divided by the number of possible ties, resulting in an average value. If values (number of connections between nodes) are dichotomized, important data are removed (connection strength between nodes), but the resulting 0–1 numbers provide a measure of network completeness that is easier to compare with other networks. *Network centralization* measures indicate how tightly the graph that depicts the social network is organized around its most central point. High in-degree centralization indicates that the group is focused inward on a few core members. High out-degree centralization means that a few core members are producing most of the connections to others. *Betweenness* is a measure of the importance of a node to connections made between other nodes. For example, if there are two clusters of individuals in a social setting, a person with high betweenness would be a member of both clusters. This would indicate that they are a 'connection point' for ideas between two clusters within the larger group. *Core–periphery analysis* extends the established centrality SNA measures of degree, closeness, betweenness and eigenvector-based measures by leveraging the concepts of group centrality and two-mode centrality (Wasserman & Faust, 1994). Core/periphery measures posit that there is some group in the core, and some other group in the periphery of a network with one centre. *Core nodes* are distinguished by creating a complete graph (where all actors are connected to all other actors).

SNA contributes an important, orthogonal perspective to our analysis of context enriched, bi-directional (both active/posting and passive/reading) event data. In previous work (Goggins et al., 2011), we described how event vocabularies and grammars derived from event logs could be used to make the indexicality of socio-technically mediated conversational moves visible to researchers more quickly. SNA adds the perspective of the networked relationships of individuals in small groups. We can focus this lens on short interaction periods of days or weeks, or on longer interaction periods of months to systematically discern social connectedness among participants, or to understand structure during different, specific types of interaction sequences. SNA complements the construction of event grammars with insight into who is connected to whom and in what way within a collaborative learning context. However, that alone is not enough to develop effective teaching analytics. We must also look at qualitative indicators of performance to strengthen and inform our computational model.

Qualitative indicators of performance in online groups

Social connections that emerge from SNA and our event logs help us to see the group structure of interactions. These are indicators of participation, not mere affiliation (i.e,, twitter followers). Knowing the structure provides one important measure of the group; we know that tightly connected groups are more cohesive and productive

(Hinds & McGrath, 2006; McGrath, Arrow, & Berdahl, 2000), and that the degree of these social connections are dependent upon social presence, or the degree to which one sees the other as a 'real person', and the tools used (Gunawardena, Lowe, & Anderson, 1997; Kreijns et al., 2004; Rourke, Anderson, Garrison, & Archer, 2007). However, qualitative indicators of performance are needed to understand the degree to which a learning group is functioning successfully. While there are many indicators of learning performance, group knowledge construction and group identity offer specific, complementary measures of technology-mediated learning outcomes. Knowledge construction is a direct measure: We can use rubrics and coding to be specific about different levels of performance and knowledge construction. Group identity, in contrast, is a complimentary measure built up from a number of less easily measured, but still empirical signals developed through our application of small group theory (Arrow et al., 2000).

Knowledge construction

Gunawardena et al. (1997) initially used content analysis to examine the construction of knowledge in an online debate. First, they examined existing techniques for identifying the negotiation of meaning and co-construction of knowledge in online learning environments. Their study determined that existing models were inadequate for understanding knowledge construction in computer-mediated communication, but through their analysis, they developed a new model for examining online interactions for the co-construction of knowledge. Their approach is based on a constructivist theory of learning, which emphasizes that knowledge construction is evidenced by the introduction of new ideas, not the regurgitation of existing knowledge. Their model includes five progressive phases: Sharing/comparing (Ph1), discovery and exploration (Ph2), negotiation of meaning/co-construction of knowledge (Ph3), testing and modification of proposed synthesis (Ph4) and agreement on constructed meaning (Ph5). Marra, Moore, and Klimczak (2004) compared Gunawardena et al.'s model for analysing content with a model established by Newman, Web & Cochran (Newman, Webb, & Cochrane, 1996), determining that the Gunawardena et al. model provides a more holistic view of discussion board flow and knowledge construction, although it requires the researcher to prepare a coding guide and procedures focused on a specific operationalization of knowledge construction in advance, as they did.

Evidence of group identity

Tajfel (1974, 1978, 1982) and Turner, Brown, and Tajfel (1979) examined how relations emerge within and between groups. In particular, they focus on the language used during conversation. Completely online group identity can be viewed as a special case of the kinds of social identity previously examined by Tajfel. In some respects, group identity is easier to parse online because it can be made visible through analysis of preserved, textual communication. Groups develop as relations between individuals, as well as relations between people who identify as members of a group. Tajfel defines four specific categories of communication (Table 1), which can be identified in the types of communication that occur in groups. By using Tajfel's categories of communication, we can better understand an individual's *sense of being in a group* as an essential function of a group. For example, if individuals are connected but do not feel they are a part of the group, how does that relate to small group performance or structure? We think that if we are able to understand how performance and structure are (or are not) related to the sense of being in a group (or 'group identity'), we can then better understand what may be occurring when we see certain structures and performances. This could eventually lead to predicting performance trajectories as well as positive interventions.

Table 1. Tajfel's Communication Types

Tajfel communication type	Description
Interindividual	Communication between two individuals in a group context. Online, this is a group discussion board. The common example from the physical world is somebody pulling another person aside at a party.
Interpersonal	Communication between two people
Intragroup	Communication between members of the same group, addressing each other as group members
Intergroup	Communication between two different groups of people

Summary of prior work

Our work builds on a synthesis of literature across disciplines, which we argue is necessitated by the nature of the challenge of scaling MOOC analytics. Collaborative and small group learning in MOOCs has been cited as a key way to successfully scale and support learning in MOOCs. This exploratory study of completely online small groups takes into account the main aspects of a group – group structure and group indicators of performance – and analyses it over time in order to propose criteria for a computational model of small group teaching analytics. This study is a systematic step toward support for the design and development of MOOCs in general, and the scaling of teaching analytics to support teacher pedagogical interventions in particular.

Course context

This article presents a subset of data gathered in study of the CANS (context aware notification system) at a large Midwestern US University between July 2004 and December 2010. This particular study focuses on a single, completely online course of 25 students. Students ranged in age from 27 to 55, and were 60% female.

Sakai and CANS

The purpose of the course was to teach design approaches for implementing computer supported collaborative learning (CSCL). The CSCL course was facilitated by the socio-technical system Sakai, with activity awareness provided by CANS (http://www.cansaware.org) and discussion forums provided by JForum. The CANS system (Amelung, 2007) was used to provide activity notification and awareness information to course members in the form of daily activity digest emails and visual feedback of relative participation of students in the course over varying periods of time. When a student logged into Sakai and posted or read a message, CANS logged this and presented summary data in the digest and through an activity monitor. All assignments and discussion to support group collaboration in the course were facilitated through Sakai, using a JForum discussion board. JForum is integrated with both CANS and Sakai.

Description of course and students

We studied an 8-week, graduate level, completely online software design course. Groups worked together after the first week for a total of 7 weeks.

The structure of the course was as follows:

1. **Week 1** – Module 1: Explore what CSCL is (Individual Activity)
2. **Week 2** – Module 2: Each group was assigned a position related to a research paper read by the class, and engaged in a debate with another group assigned an opposing position.
3. **Week 3** – Module 3: A Group activity to construct a coherent story of past online learning. First, students described individual experiences. Then, as a group they were asked to design an online experience that is improved, using available 2D and 3D collaboration technologies
4. **Week 4** – Continue Module 3
5. **Week 5** – Module 4: A Group activity to design a 2-day online learning module to be delivered to 2 other teams in Module 5. This module involved the most intense period of creative collaboration among the groups.
6. **Week 6** – Continue Module 4
7. **Week 7** – Module 5: Groups delivered modules designed in Module 4 to two other student groups. The groups also participated in the module designed by a different group. During this period, each group of three to four students had three different, unrelated work tasks to attend to.
8. **Week 8** – Module 6: Group and individual reflections.

Data and methods

This study is a multiple case design focused at the small group unit of analysis (Yin, 2009). Our findings are built from six categories of data: interview data, group efficacy survey data, content analysis of discussion board posts, ethnographic field notes, student assignments and SNA of participant interactions (CANS). The interview and survey data incorporate participant reflections on activity, while the content analysis, field notes and network analysis are researcher observations and analysis of behaviour. Student assignments are evaluated with a rubric, which we prefer as a more robust and fine-grained assessment than final grades. Fourteen purposively

Table 2. Data and Corresponding Analysis Methods

Data	Construct[a]	Analysis methods
Discussion boards	• Knowledge construction • Identity	Content analysis
CANS logs	• Structure	Social network analysis
Interview transcripts	• Identity • Knowledge construction	Open and axial coding
Field notes	• Identity • Knowledge construction • Structure	Open and axial coding
Group efficacy survey	• Identity	Two-tailed t-test and case description
Student assignments	• Knowledge construction	Scoring and coding against a rubric developed in a previous version of the course

[a]All constructs are at the small group unit of analysis.

sampled students assigned to eight different groups were interviewed three times. Each of the 42 interview sessions lasted between 40 min and 1 h and 40 min. All interviews were transcribed. Interview questions focused on how knowledge was constructed and the identities developed by each of the groups. The integration of these six data sources from eight cases in our analysis provides triangulation for our findings, enhancing internal, external and construct validity (Yin, 2009).

Our analysis was both qualitative and quantitative (network analytic). Our qualitative data analysis included the importing of interview transcripts, discussion boards, course reflections, chat transcripts and wiki data into NVivo 8, and the performance of ethnographically informed open coding (Charmaz, 2003). More than 500 distinct codes emerged from the coding process, with more than half of those addressing the social interactions within and between the members of the eight completely online groups (COGs) in the course. All of these artefacts and the resulting codes were then refined through constant comparison to arrive at a set of core collaborative themes within this course. Table 2 summarizes the data used, the constructs they apply to and methods of analysis.

Who interacts with whom (network analysis of participation)

Network analysis was performed using the unique, bidirectional logs (read and post) captured in CANS (Goggins, Laffey, Amelung, & Gallagher, 2010; Goggins et al., 2010), and was used to describe how the structure of small groups and the entire course changes over the duration of the collaboration. This analysis provides researchers with an awareness of group structure that the members may be able to intuit but have no direct representations of, and which will be described in context with group identity development, efficacy and performance.

What happens within interactions (quality indicators and measures)

Three types of qualitative analysis were conducted for this study. First, we performed content analysis on discussion board posts. A total of 1687 discrete discussion board posts were coded at the post unit of analysis using both Gunawardena et al.'s (1997) coding scheme for knowledge co-construction and a coding scheme based on Tajfel's (1978, 1982) constructs of social identity.

Krippendorf's reliability formula, referred to as Krippendorf's alpha (Krippendorff, 2004), was calculated for both the knowledge co-construction codebook and the social identity codebook for all eight COGs. Krippendorf's alpha is a measure of the reliability of the codes chosen by two raters. Raters first assign codes to a post independently, then get together to discuss differences. Krippendorf's alpha compensates for agreement reached by chance in content analysis. For knowledge co-construction, the Krippendorf's alpha showed a coefficient of 66.9% for initial codes and 96.9% for codes after reliability discussions. For the social identity codebook, the Krippendorf's alpha showed a coefficient of 92.9% for initial codes and 99.7% for codes after reliability discussions.

Our qualitative data analysis included importing interview transcripts, discussion boards, course reflections, chat transcripts and wiki data into NVivo 8, and conducting ethnographically informed open coding (Strauss & Corbin, 1998). More than 500 distinct codes emerged from the coding process, with more than half of those codes addressing the social interactions within and between the members of the eight COGs in the course. All of these artefacts and the resulting codes were then refined through constant comparison to build case descriptions (Yin, 2009) for all eight COGs.

Group identity

The codebook for social identity included four discrete codes that map to communication practices in Tajfel's (1978) and Tajfel's (1982) theory of social identity:

- Interpersonal
- Intragroup
- Interindividual (an aside between two individuals within a group context)
- Intergroup

To identify identity-oriented characteristics (identity) and level of knowledge construction (performance) within each group, we examined the type of communication between group members. Two raters applied a four-category, non-hierarchical codebook for group identity to each post, and an 18-category, hierarchical codebook of knowledge construction at the discussion board post unit of analysis. The two raters showed a Krippendorf's alpha coefficient of 92.7% before rater reconciliation, and 99.7% after rater reconciliation. Krippendorf's alpha coefficient is a superior measure of inter-rater reliability in this context when compared with others like Cohen's Kappa because it takes into account both initial agreement and negotiated agreement between raters (Marra et al., 2004; Moore & Marra, 2005).

Knowledge construction

The knowledge co-construction codebook contained 18 distinct codes, grouped under the five high level categories initially described by Gunawardena et al. (1997):

- Phase I – Sharing/Comparing Information (Ph1)
- Phase II – Exploration of dissonance (Ph2)
- Phase III – Negotiation of Meaning (Ph3)
- Phase IV – Testing of proposed co-construction (Ph4)
- Phase V – Application of newly constructed meanings (Ph5)

Finally, group deliverables for Modules 2 and 4 were analysed using a detailed rubric, built from analysis of a prior instance of the same online course. Scores were derived for each deliverable, and assigned to each of four group work products by two raters. The raters then reconciled differences in rating, reaching 100% agreement on the rubric scores.

Reflexive integration of network analytics and quality measures

We used a mixed methods approach described as Group Informatics (Goggins et al., 2013) to reflexively integrate our analysis of knowledge construction, group identity and network position. The network diagrams presented in the findings are not mere restatements of the raw trace data generated by CANS. Rather, they include weighting based on the time difference between two posts, the length of the response and the knowledge construction contained in a response to indicate the total network measure. We worked through these weighting procedures such that each node has centrality measures that are richer than what is typically found when SNA is applied to learning data. (See Goggins et al., 2013 for a complete explanation of weighting strategies.) We also surveyed each group using a four-item survey that measures 'group efficacy' before, during and after collaboration (Fuller, Hardin, & Davison, 2007; Gibson, Randel, & Earley, 2000). This instrument is used to triangulate network structure across all groups as a measure of performance in the third research question.

Research questions

We explore the connection between learning performance (knowledge construction and group identity), and group structure (SNA of bi-directional log data) in a particular context in order to advance understanding of how to design teaching analytics for MOOCs. We focus on three research questions:

1 What social network structures are formed within online small groups and across online small groups during completely online group work?
2 How and to what extent do learning performance and group identity differ among small groups involved in a completely online course?

3 How and to what extent do performance indicators in completely online groups correspond with small group structure (social networks)?

Findings

We find a number of potential signals of differences in small group performance in MOOCs using a curriculum designed for small group work. Our exploratory study illustrates how MOOC teachers could view the relationship between group performance and structure for interpretation in new ways. We do not claim to prove that groups possessing specific structural properties as evidenced by their interactions in an online learning system necessarily perform at a certain level. Instead, our findings show an array of patterns that are not presently visible to MOOC teachers. What our study makes visible through mixed methods analysis offers cues for the types of learning analytics that may prove useful in the future, and are unlikely to be uncovered through computational analysis alone (Borge & Goggins, 2014; Goggins, Laffey, & Galyen, 2009; Graves et al., 2014).

Social structures in completely online small groups

Q1: *What social network structures are formed within online small groups and across online small groups during completely online group work*?

When we are interested in patterns of group structure, the first question becomes: Does all this network analysis yield a result that is different from and more useful than simply counting who clicks or types the most? Figure 1 provides an overview of the level of activity of each group, including reads and posts, in Modules 1–6. Keep in mind that Module 1 is an individual activity lasting one week, and the remaining modules are small group activities lasting 1 to 2 weeks. Get-Along Group (all groups were given pseudonyms for purposes of analysis and reporting) shows consistently high participation levels in the core modules, 4 and 5. Other than that, no clear pattern emerges from clicking alone.

With the limited utility of pure post counting established in this context, we move on to the structural analysis methods at the core of Research Question 1. The analysis for our first question focused on building

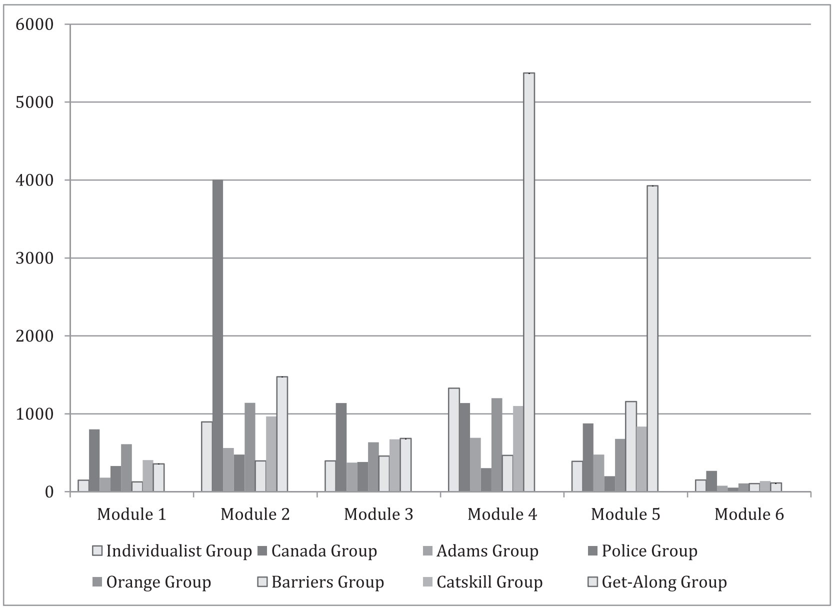

Figure 1 Raw Participation Counts by Group and Module Are Presented Here. The Three Focal Groups Are Highlighted Using the Same Pattern and Colour Scheme. One Can See That the Closeness of Participation Among Members Is Not Revealed in the Same Way Through Analysis of Raw Posting Counts as It Is Through a Weighted Network Analysis, Illustrated in Figure One. Specifically, Examining Total Participation in Each Module, We See That Individualist Group Members Sometimes Participate Extensively, Although in Figure One It Is Clear They Are Not Working Closely with Each Other. This Figure Also Illustrates How Get-Along Group Is, by a Substantial Margin, the Highest Participating Group During Key Modules of the Course, Modules 4 and 5

understanding of the social structures made visible through SNA of a weighted network. The weighted network is informed by the difference in time between posts (closer together in time indicates a stronger tie), and the degree of group identity and knowledge construction in a particular post. Read behaviour is weighted solely based on the time distance between the post and the read, and counted at one half the connection weight of response post (Goggins et al., 2010). The network data are not derived directly from the traces of behaviour, but from a reflexive, qualitative process of analysing interactions between members, then using that analysis to inform connection weighting. Here, as suggested in Goggins et al. (2013), we use time distance between interactions and the interactions themselves to build a model for how to weight individual communication acts. For example, ten comments occurring 2 min apart on average will lead to a stronger connection than ten comments, a day apart on average; and so on. Figure 1 reveals a structural closeness among two groups (a high and low performing group) as well as great distance between the third group, Individualist, which performs poorly on assignments, but occasionally demonstrates a higher level of knowledge construction on the discussion board.

To what extent do social network structures change over the course of group work?

Given our calculated weighted network statistics, the key to representing structure is to do so in a way that helps MOOC teachers understand differences at multiple levels (e.g., course as a whole, small group, and individual). Sociograms are a common way of representing social networks, but our analysis and review of visualizations with online teachers suggests that sociograms are necessary but insufficient for understanding structure. The first important step is the weighted network calculations; to reflect in the quantitative analysis key dimensions of how qualitative behaviour are experienced as structure within the groups. Our extensive interviews contributed to the specific weighting implementation.

Figure 2 represents network density. The maximum value (1) would occur if every member of the course read or responded to every post from every other member of the course. Next, it is important to understand the level of network 'tightness' at the course level over time.

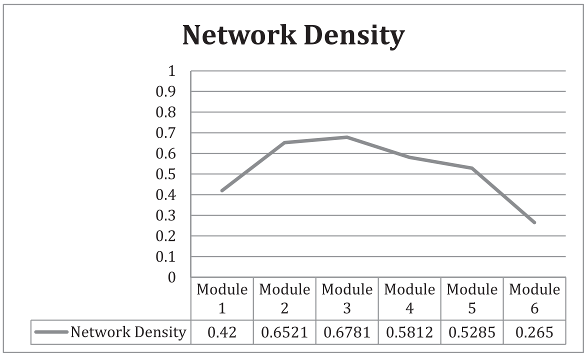

Figure 2 Overall Social Network Density Trends by Module

The trend is a high-level view that instructors can connect implicitly to the structure of activity, influences of a particular learning management system and their students. In this course, we see that as group work progressed through the modules, the overall course network became less dense. In a course designed for small group work, this is a signal that, in general, the groups are progressively working more closely within themselves, and relying less on course level information and discussion. This could reasonably be valenced as a positive overall trajectory.

After examining the network structural trajectory of the course as a whole, it is important to understand different structural patterns that emerge for different groups. There are two statistical indicators that illustrate the degree to which individual members of a group are participating and contributing at different rates. The valence of these rate differences in this particular course is discussed in research question three; and is context specific to the curriculum in this course. In other words, Figures 3 and 4 illustrate that the three (of eight) groups we focus on in order to provide an article of reasonable length show variation in Network Group Centralization

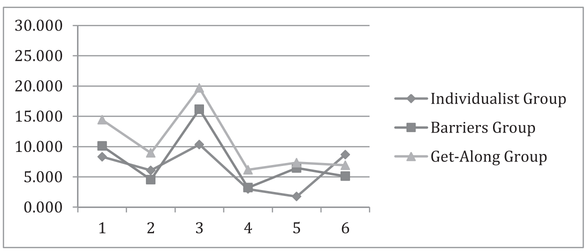

Figure 3 Network Group Centralization for All Three Case Study Groups. The x-Axis Represents Module Number; the y-Axis Represents Group Network Centralization

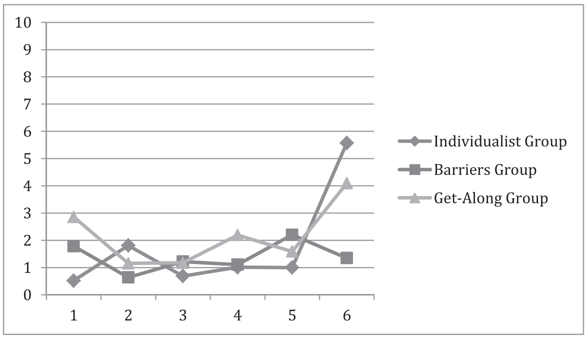

Figure 4 Betweenness Centralization Measures for Three Case Study Groups. The x-Axis Represents Module Number; the y-Axis Represents Group Network Centralization

and Network Group Betweenness Centralization. Over time the variance in Network Group Centralization suggests differences among members in degree centrality. Differences in betweenness centrality among members are also clear; the higher the line, the greater the distinction between members within the module indicated on the x-axis (Wasserman & Faust, 1994, pp. p.176, 192). Figures 3 and 4 illustrate that Individualist group consistently remains low in betweenness centrality and degree centrality. This suggests that, with the exception of Module 6, Individualist group focused 'inward' (on their own group). This is consistent with interview and survey data from this group's members and inspires their name.

Higher y-axis marks indicate that the groups have individuals who are interacting with different levels of weighted intensity and frequency. These variances in-group structure correspond with our qualitatively assessed group names. 'Get-Along' group is highly social and typically at the top of overall degree centralization in the course. Barriers and Individualist group are flat on group betweenness, but vary somewhat on overall degree centralization. This indicates that most of their interactions are within their groups. Making such group level differences in structure visible through graphs like these could provide useful, powerful cues to MOOC instructors.

When group participation levels vary by individual members, knowledge of who the different members that are grouped together are becomes a key piece of information for teachers. Borgatti, Everett, and Freeman (1999) developed a multiple sampling methods for identifying cohesive subgroups in small-scale social networks, called 'Factional Subgroup Analysis'. They regard the

Table 3. Group Assignment Rubrics Tiered as 'High' (Green), 'Medium' (Yellow) and 'Low' (Red) Performance

Module	Members in the same group	Run percentage
Barriers Group		
Three	Steven and Malakai	85%
Four	Steven, Malakai & Yoda	14%
Four	Steven & Yoda	14%
Five	Steven & Yoda	57%
Five	Steven & Malakai	14%
Individualist Group		
Three	Cameron and Rabbit	14%
Four	Justin, Cameron & Rabbit	14%
Four	Justin & Cameron	57%
Four	Justin & Rabbit	14%
Five	Justin, Cameron & Rabbit	43%
Five	Justin & Cameron	28%
Five	Justin & Rabbit	28%
Get-Along Group		
Three	Joplin & Sally	25%
Three	Sally & Tommy	25%
Four	Sally & Tommy	84%
Four	Joplin & Sally	16%
Five	Joplin, Sally & Tommy	14%
Five	Sally & Tommy	14%

measurements produced as requiring qualitative analysis and tuning, but this, combined with repeated execution of the algorithm (which can be set in a parameter in UCINET) leads to more robust subgroup indications. For each module, each group was iterated over 1000 times in UCINET, producing the results illustrated in Table 3. We can see that Steven acts as a consistent bridge between other members of barriers group; suggesting his role is mediation between other members, or coordination work. The high number of cohesive subgroups in Individualist Group corresponds with their qualitatively validated sense of individual, independent operation with limited coordination overhead; just as Steven's work as a mediator in Barriers group is suggested through this analysis. Finally, Get-Along Group, which is the most socially active, shows Tommy as a member of a subgroup in each module, although Tommy and Sally form a strong subgroup in Modules 3 and 4. This is generally consistent with the findings suggested by Figures 3 and 4 as well: not all members of Get-Along Group participate in an equal way, and it appears Sally and Tommy are particularly well connected.

Finally, Figure 5 presents the classic, structural view of a social network: The sociogram. We see here that Individualist Group stands out as being distant –

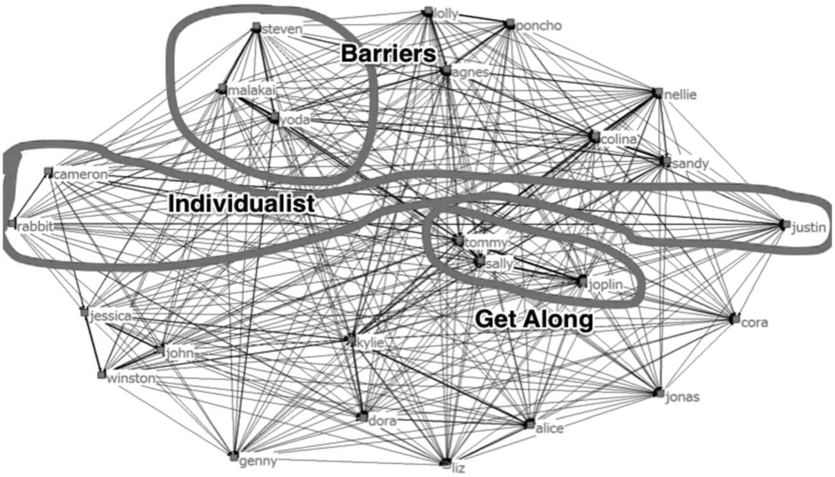

Figure 5 Social Network Diagram of All Members Based on Euclidian Distance for Modules 3 Through 5 (Darker Lines for Stronger Ties), which Constitute the Most Group Work Intensive Part of the Course Examined

particularly Justin – and Get-Along Group is both clustered closely together and near the centre of the course level sociogram. This corresponds with their high level of overall activity, depicted in Figure 1. The closeness of Barriers Group on the periphery of the network illustrates how the nature of being assigned to a group can influence how that small group appears in the sociogram. So, while helpful for illustrating group structure, the sociogram is not sufficient for characterizing the different structures of each small group. Results for RQ1 clearly illustrate that structure changes over time in an online course, and these changes can be made usefully visible to teachers in online courses in general, and MOOCs in particular.

What happens in interactions: differences in quality performance indicators among online small groups

Q2: *How and to what extent do learning performance and group identity differ among small groups involved in a completely online course*?

We examine group performance through a three part lens of: (a) artefact assessment using a rubric; (b) assessment of knowledge construction in online discussions using a construct validated coding scheme; and (c) indicators of group identity expressed in online discussions, using a construct validated coding scheme. Our findings show that performance differs across all three performance indicators. Further, we show that each of the three parts in our proposed set of performance indicators provides a distinct signal to the teacher that could together be automated to accelerate understanding of small group work in MOOCs.

Knowledge construction through artefact assessment

We operationalized knowledge construction using a rubric for three pivotal group assignments and analysis of the level of knowledge construction present in each small group's discourse. Table 3 shows the rubric scores for each of the eight groups. The performance on each of three assignments is tiered per assignment and categorized as 'high' (green), 'medium' (yellow) or 'low' (red) performance. A consolidated rating across all three assignments is indicated as a 'total' in the last row. No group performs 'high' on all three assignments; Barriers Group is the highest rated with two of three assignments in the highest tier.

Knowledge construction through content analysis of discussion board posts

For a second view of performance, we evaluated small group discussion performance for the degree of knowledge construction. Here we used an 18-item, five-class-tiered knowledge construction rubric that has been validated in a number of studies of online discussion board knowledge construction (Gunawardena et al., 1997). In this view, we focus on three of the groups, purposively sampled based on maximum variation in assignment performance (see Table 4). There were no examples of

Table 4. Knowledge Construction Measures for Three Representative Groups

	Overall	Module 4	Module 5
Barriers Group			
Ph1	88.2%	96.0%	80.2%
Ph2	9.4%	4.0%	14.8%
Ph3	2.5%	0.0%	5.0%
Individualist Group			
Ph1	81.4%	85.1%	90.9%
Ph2	10.3%	11.8%	10.1%
Ph3	8.2%	3.1%	0.0%
Get-Along Group			
Ph1	85.8%	84.8%	91.4%
Ph2	9.1%	9.0%	5.1%
Ph3	5.1%	6.2%	3.5%

Table 5. Individual Knowledge Construction Scores in Discussion Boards

	Ph1	Ph2	Ph3
Barriers Group			
Malakai	77.5%	16.3%	2.5%
Steven	93.8%	4.2%	2.1%
Yoda	88.9%	4.9%	2.5%
Group total	88.2%	9.4%	2.5%
Individualist Group			
Cameron	65.4%	13.5%	9.6%
Justin	92.9%	0.0%	7.1%
Rabbit	83.8%	5.4%	5.4%
Group total	81.4%	10.3%	8.2%
Get-Along Group			
Joplin	78.7%	16.0%	5.3%
Sally	85.7%	7.6%	5.9%
Tommy	87.6%	6.5%	4.3%
Group total	85.8%	9.1%	5.1%

knowledge construction in the highest two phases (Phases 4 and 5); a finding that is consistent with the analysis of the team who developed the knowledge construction through discourse indicator we reference (Gunawardena et al., 1997). We focused particularly in Modules 4 and 5, which were the culmination of group work through the semester, and the point in the course from which we drew two of the three assignments that we evaluated using rigorous rubrics. One will immediately notice that Individualist Group is the highest performing group in our analysis of knowledge construction (Table 4), but the lowest-performing group in terms of artefact evaluation (Table 3). Barriers Group, in contrast, performs at a high level on the artefact analysis, but their discussion board knowledge construction varies considerably (Table 4). Also, barriers group also performs low on the 'Assessment' task in Module 5 (Table 3). Together, these indicators of knowledge construction suggest that not only does variance occur in small group work, but that the trajectory may not be consistent.

The absence of a consistent indication of performance across multiple measures is not problematic. Instead, these indicators provide a foundation for the development of learning analytics that serve MOOCs because the most accurate predictors do not come from a single model, but from the integration of multiple models (Silver, 2012). This finding suggests an entry point for building robust models of knowledge construction performance in MOOCs.

Another model for knowledge construction through discussion boards that we find shows, that although the groups vary considerably (Table 4), there are also variations in the performance of individuals within groups. Most significantly, each of the three groups examined had one member who performed significantly more PH2 level knowledge construction than the other two group members (Table 5 and Figure 6).

Figure 6 highlights aggregate individual and group differences in knowledge co-construction during module four. First, notice how little Barriers group works at levels above Ph1/a. Next, notice that Barriers and Individualist groups have a similar number of total posts (Figure 6, y-axis), but how the knowledge construction is spread into Ph2 and Ph3 levels for Individualist group. Finally, although on a percentage basis (Tables 4 and 5) Get-Along group is about even with Individualist group in knowledge co-construction, the total number of higher level co-constructive acts is greater. A key will be to detect when a group's high level of communication corresponds with knowledge construction, and when it does not.

Group identity through text analysis and interviews

Group identity is a third component of performance, operationalized here as the degree to which group members expressed themselves either toward the group, other individuals or parts of the group; and member reflections on their group identity as culled through open and axial coding of interviews with each group member in the Barriers, Get-Along and Individualist groups.

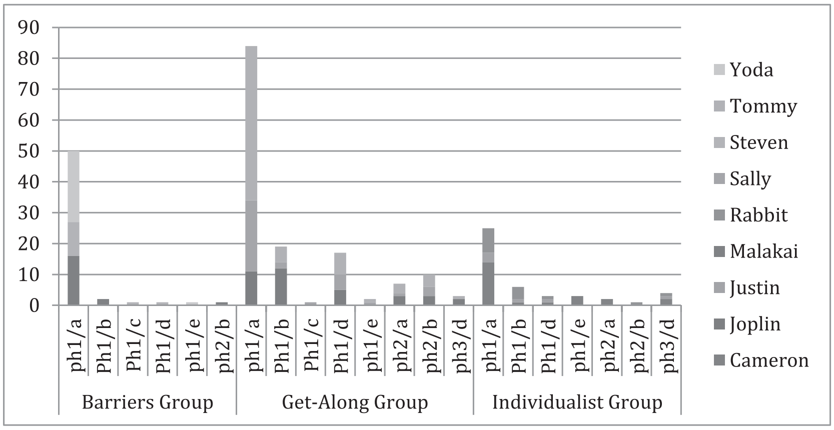

Figure 6 Module 4 Gross Knowledge Construction Across Groups and Members

Table 6 summarizes our findings about the three focal groups in our study. There are two notable characteristics in the comparisons of group identity between these three groups. First, we see that the groups who encountered the most difficulty and distrust during the course, Barriers group, communicates far less at the small group level than Individualist or Get-Along Group. Second, we see that Individualist Group and Get-Along group, while similar in terms of the manner in which they communicated, each described fundamentally different experiences during their interviews. Computational linguistic analysis to identify the type of communication direction could be, in this case, potentially useful for detection of severe trouble in a small online group, but less effective for discerning subtle differences.

Summary: research question 2

The tripartite measure of performance we construct illustrates that different perspectives and indicators contribute a variety of information about student performance and each may be valuable for teachers in online courses. Our findings of incongruence between knowledge construction evidenced in artefacts, knowledge construction evidenced through discourse and group identity make it clear that: (a) such performance differences can be identified through analysis of trace data, and (b) multiple perspectives and indicators will be required for teachers to take action based on analytics. Our third research question aims to identify what, if any, meta-indicators may exist in the comparison of structure and performance that could prove useful in MOOC scale online learning.

Table 6. Group Identity in Discussion Board Communication and Interviews for all Three Case Study Groups

		Barriers Group	Individualist Group	Get-Along Group
Group identity scores through discussion board coding	Small-group communication	59.9%	85.1%	85.7%
	Interpersonal communication	39.1%	13.8%	12.2%
	Inter-individual communication	1.0%	1.1%	1.3%
Group identity themes from open and axial coding of interviews		• Strained interaction • Struggle for control • Absence of mutual respect	• Low coordination • Individual work presented/little collaborative work	• Active social comparison with other groups • Work made visible during construction

Table 7. Group Module 4 Performance and Degree Centrality Means

Group	Out degree centrality	In degree centrality	Module 4 rubric score
Barriers mean	7.39	8.78	64.00
Catskill mean	9.20	9.26	58.00
Adams mean	6.09	6.58	54.00
Orange mean	6.55	6.09	54.00
Canada mean	7.64	5.01	46.00
Get-Along mean	11.32	9.80	38.00
Police mean	3.26	4.03	35.00
Individualist mean	3.77	4.88	31.00

Table 8. Out Degree Centrality and Group Efficacy

Group	Out degree centrality	In degree centrality	Group efficacy
Get-along mean	11.32	9.80	1.17
Catskill mean	9.20	9.26	1.50
Canada mean	7.64	5.01	1.31
Barriers mean	7.39	8.78	2.67
Orange mean	6.55	6.09	1.67
Adams mean	6.09	6.58	1.00
Individualist mean	3.77	4.88	1.50
Police mean	3.26	4.03	2.75

Reflexive analysis: the relationship between performance indicators and structure

Q3: *How and to what extent do performance indicators in completely online groups correspond with small group structure* (*social networks*)?

Our performance indicators come from bidirectional trace data, content analysis, and module rubric outcome scores. We find a strong connection between low degree centrality as discerned from network analysis of bidirectional trace data and performance in the course. Table 7 illustrates this relationship clearly. Furthermore, a first critical question for this finding is likely to be, 'Can we discern the same results from simpler analysis of overall participation? Are the low degree centrality teams also the lowest in participation?' A contrast between Figure 1 and Table 7 shows the answer is decidedly, 'no'.

A similar, but somewhat fuzzier relationship between performance and high centrality groups is also visible in Table 7, although there is greater ambiguity in the cases of Get-Along and Canada group. The data show, however, that for the highest performing and lowest performing groups, there is a relationship (though not linear) between performance and network centrality at the outer edges of these measures. Groups with the highest rubric scores also had the highest out degree and in degree centrality. Groups with the lowest rubric scores had the lowest out degree and in degree centrality. The four groups in the middle for rubric scores had mixed in degree and out degree centrality. This suggests that network centrality is a helpful indicator of group edge cases at both the high and low end. For non-edge cases, it is less clear from the data, suggesting initial design iterations based in this finding should focus on the edges: The highest and lowest performers. Further research and data analysis is likely to prove useful in teasing out distinguishing characteristics in middle cases.

Group identity, noted as a measure of performance in finding two, could be teased out with some efficiency through ongoing surveys on students in MOOC learning groups. Table 8 illustrates that a short instrument like the one we used does produce a correspondence between degree centrality and higher levels of group efficacy (reflected in lower scores). A future experiment should explore this relationship further.

Table 9 takes a step back to view patterns from all research questions. As demonstrated in the table, the pattern is not linear, though there are some clear differences between these three very distinct groups. The Get-Along Group was highly social and productive, as evidenced by the network analysis and qualitative analyses. The Individualist Group, a very insular group with low coordination yet still relatively high levels of co-construction, did not need to communicate frequently in order to produce relatively good outcomes. The knowledge co-construction and the dominant identity subtype in their communication are good indicators that this group is indeed 'individualist': insular as demonstrated by the centrality data, productive, not highly active, but during those active times they are co-constructing knowledge. The Barriers Group, which would be concerning to instructors, are highlighted by their low efficacy, low levels of knowledge construction, and a lower ratio of group to interpersonal identity subtype communication.

Overall, research question three focused on the relationship between structure and performance in online learning groups, and provides a number of hints for future research and development in MOOCs. Focusing on

Table 9. Summarizing and Synthesizing Findings Across Research Questions, Focused on the Integrative Research Question (RQ3)

	Barriers Group	Get-Along Group	Individualist Group
Betweenness	Flat (within group)	High (social with outside group)	Flat (within group)
Out degree	High	High	Low
In degree	High	High	Low
Group efficacy	Low	High	High
Module 4 performance	Medium	High	Medium
Post frequency	Moderate	High	Low
Knowledge construction	Low	High	High
Identity	• Strained interaction • Struggle for control • Absence of mutual respect	• Active social comparison with other groups • Work made visible during construction	• Low coordination • Individual work presented/ little collaborative work
Identity: dominant identity subtype in communication	Interpersonal and group	Group	Group

the edges (or distinct groups which are more extreme), and providing lightweight surveys on how groups are conceptualizing themselves as effective or not effective are two promising mechanisms for providing teachers with feedback and easily understood indicators they can act on during the execution of the course. The patterns discussed in this article, while not yet generalizable, demonstrate that there is room for further research. We envision this further research providing instructors opportunities for awareness and intervention in MOOC courses by: (a) utilizing automated content analysis for identity and knowledge construction, and (b) pairing that analysis with network analysis of bidirectional data using advanced algorithms. In all cases, the examination of the combination of the indicator, the course content/pedagogy and the teacher's judgement are needed for a good result.

Discussion

Systematically scaling MOOC learning analytics

The promise of learning analytics for MOOCs is innately appealing to researchers, practitioners and policy makers. Beyond mere efficient assessment, effective analytics in a MOOC environment can improve the efficacy of learning on a large scale and potentially provide education to more people at lower costs. Our findings suggest that the practice of developing analytics for MOOCs can pragmatically be conceptualized in the early stages as helping teachers to identify difficulties early by developing small group focused pedagogy and attending to network analytic representations of how those group interact with each other and the larger MOOC. A next stage in our work is to scale small group analytics out to MOOC scale courses.

Role of integrated methods: qualitative and quantitative

Our findings are a prototype of MOOC teaching analytics on a small scale using both quantitative and qualitative methods. When one hears 'learning analytics', automated, quantitative measures are foregrounded. In our case, we show how the integration, triangulation and reflection on multiple indicators of performance and structure provide a set of information that becomes useful in the context of active teacher reflection.

Implications for design

Our findings and the context of our study make the case that there is value in prototyping analytics on a small scale to identify their potential for being scaled up to MOOCs; and that teaching analytics as a research aim avoid some of the risk of decontextualizing the design of learning analytics from the broader MOOC context. This learning analytics context is the intersection of pedagogy, student interactions, course context, the analytics indicators themselves and teacher judgement. Collaborative learning as a pedagogical framework is, we find, a key component of what will be required to scale MOOCs and the analytics tools built up around them.

The kinds of analytics required to support small group learning in MOOCs must address four key gaps in the current state of the art. These gaps arise from the unexplored relationship between group performance, group structure and group identity (Gross et al., 2005).

First, prior studies of small, online learning groups do not relate the temporality of group development as a central aspect of analysis, yet group performance, structure and identity are widely understood to change over time (Gersick, 1988; Knowles & Knowles, 1955; Tuckman, 1965). Second, learning performance is not consistently measured, if it is measured at all. Student grades are frequently used as a method of convenience, but their limited utility as a measure for learning performance is well documented. To understand small online learning groups, we would need to study them over time using multiple measurements and include learning performance (outcomes). Learning analytics would need to address this temporality and be able to demonstrate changes over time. The study presented here accomplishes these aims by focusing on module specific temporal changes.

Third, there is wide variation in the meaning of words like 'online' and 'CSCL'. In some studies, small online groups are those who meet partially online and partially face-to-face (Cho, Gay, Davidson, & Ingraffea, 2007; Cress, Barquero, Buder, & Hesse, 2005; Johnson, Suriya, Yoon, Berrett, & Jason, 2002; Michinov & Michinov, 2007, 2008; Michinov, Michinov, & Toczek-Capelle, 2004) and in other studies the small groups may actually be composed of geographically distributed subgroups (Cadima, Ferreira, Monguet, & Ojeda, 2010). Only a few studies look explicitly at the completely online case (Goggins et al., 2010). Such differences in socio-technical context are widely understood to have a material effect on group experience (Dourish, 2004; Nardi, 2010), but consideration of these effects is glossed over in much work that examines these phenomena. Similar ambiguities exist around the definition of 'MOOC', and could subject MOOC analytics research to the same challenges faced in other heterogeneous, online learning contexts (Goggins 2012).

Fourth, the emergence of group identity, group efficacy and group practices in the completely online case is not described elsewhere, yet these dimensions are at the core of what it means to be a group. These correspond to McGrath's (1991) three functions of a group, and yet understanding small groups, especially through learning analytics, has yet to study and take into these functions in order to make the analytics meaningful and powerful.

Conclusion: the future development of social sensors

To address both the gaps, and our implications for design, we turn to a broader literature for inspiration. Social media research focused on monitoring, aggregating and analysing activity from mass participation in social media (Kwak, Lee, Park, & Moon, 2010; Priedhorsky et al., 2007) is one promising source of inspiration in the development of learning analytics. For example, we know that under some circumstances (disasters and citizen participation, for example), people act as social sensors of the world around them by sharing information; thus leveraging the scale of the online population. This leveraging then serves as a potential solution for general scalability issues associated with analytics of online behaviour (Bell, McDiarmid, & Irvine, 2011; Christakis & Fowler, 2010; Kim, Chu, Brdiczka, & Begole, 2009; Lazer et al., 2009). Examples from social media demonstrate how useful information can be culled from a vast ocean of data.

When people contribute '*any source of information that can be identified in modern social networking and Web tools that expresses some situation or fact about users and their social environments*', we can consider them to be, in a sense, social sensors (Rosi et al., 2011). In a learning context, thinking about people as social sensors could be useful for the development of learning analytics that aim to increase awareness of small, online learning groups and their learning trajectories. To enhance learning, we need to make individual, group and course-level factors that contribute to learning visible to teachers and students. Moving from raw trace data to learning analytics and social sensors requires us to identify the signals, or data from those sensors that have utility for learning and instruction (Goggins & Petakovic, 2014).

Developing social sensors that make students and teachers more aware of behaviour that is associated with learning requires thinking about where these signals of learning behaviour might exist in MOOCs. Prior research focused on smaller-scale learning analytics – dozens of students instead of thousands – suggests one possible approach for the development of robust, scalable learning analytics. Specifically, awareness of the read behaviour ('listening or lurking') of small learning group members is one promising place where user behaviour can act as a *social sensor* for network position of individuals and groups in a MOOC (Goggins et al., 2011; Wise et al., 2012). At a conceptual level, Paredes and Chung (2012) apply SNA, measurements of learning and content classification to operationalize situated learning theory as a basis for modelling socially informed learning analytics. Together with available 'read' data, social sensors and dynamic models of learning behaviour are promising, but unfulfilled developments for increasing small group awareness with the aim of measuring and managing learning in MOOCs. This article has sketched a way forward.

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