The Pennsylvania State University

The Graduate School

EXAMINING THE EFFECTS OF LEARNERS' BACKGROUND AND SOCIAL NETWORK POSITION ON CONTENT-RELATED INTERACTION VIA THE MOOC PLATFORM

A Dissertation in

Learning, Design and Technology

by

Qiyuan Li

Submitted in Partial Fulfillment
of the Requirements
for the Degree of

Doctor of Philosophy

August 2019

The dissertation of Qiyuan Li was reviewed and approved* by the following:

Priya Sharma
Associate Professor of Education
Dissertation Advisor
Chair of Committee

Roy Clariana
Professor of Education

Simon Hooper
Professor of Education

Runze Li
Professor of Statistics

Susan Land
Director of Graduate Studies, Department of Learning Performance and Sytems

*Signatures are on file in the Graduate School

ABSTRACT

This study aimed to investigate the relationship among MOOC learner's background, social network position and level of interaction. More specifically, it has two goals: (a) to find, at the individual level, the relationship among each learner's background, social network position, and interaction; and (b) to find, at the thread level, how the level of diversity among learners in a single thread affected their interaction with one another.

To achieve these goals, this research compared the magnitude and significance of factors influencing interaction, including background and social network position and their indicators. Prior research has largely focused on the effects of background and social network position on quantitative features of interaction, such as the number of views, replies, and votes, as well as the duration of threads. This research expanded the scope of the investigation to consider qualitative features such as cognitive engagement level (ACI score) and sentiment polarity in interaction. It also evaluated the extent to which each of these factors influences interaction. In practice, background and social network position could be associated with interaction, but MOOC instructors should be aware of the conditions that enable this to occur. Instructional plans encouraging learners to connect with their peers may lead to constructive activities but not interactive activities, the latter of which are based on peers' contributions. High levels of cognitive engagement in interaction are generally predicted by negative sentiment. Therefore, negative words are also significant components of interaction in higher-level cognitive engagement. This study reminds MOOC instructors that the posts and comments constructed by negative words are also worth noting. The English-language proficiency levels of individual learners strongly predicted interaction level. MOOCs usually attract a large number of learners whose native language is not English; these learners comprise a subgroup that merits greater attention.

This study demonstrated that diversity of background only weakly contributed to a decrease in interaction level for learners. Although negative, the effects of social network position diversity on interaction were generally weak. The top 20% of threads even showed a positive contribution of social network position diversity to interaction. Thread level diversity did not significantly impair interaction level.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ACKNOWLEDGEMENTS

I received a great deal of support and assistance during the writing of my dissertation. First, I would like to thank my advisor, Dr. Priya Sharma, who supported me going through so many unexpected challenges. I would like to express my deep gratitude to my dissertation committee member, Dr. Roy Clariana, Dr. Simon Hooper, and Dr. Runze Li. I am very grateful for the flexibility to allow me to have sufficient time extending this research topic, and for all the great advice and suggestions. I also want to thank Yu Xia for her efforts in the content analysis. It is impossible to finish this research without the help from any of you. I dedicate this dissertation to my parents, Hengqiang Li, and Yacong Zhang, for their love and patience to support me through this long journey for years. Your unconditional support backs me up for this and all future challenges in my journey to achieve my goals.

Chapter 1

INTRODUCTION

Massive open online courses (MOOCs) have drawn widespread attention since their introduction via the course Connectivism and Connective Knowledge, which was facilitated by Stephen Downes and George Siemens in 2008 (Deng & Benckendorff, 2017; Liyanagunawardena, Adams, & Williams, 2013; Uden, Sinclair, Tao, & Liberona, 2014). A MOOC is defined as an open, registerable online curriculum with open-ended outcomes (McAuley, Stewart, Siemens, & Cormier, 2010). The audience for MOOCs has grown dramatically since MOOCs' introduction in 2008. Indeed, by the end of 2016, there were 58 million learners enrolled in the 6,850 MOOCs provided by over 700 higher-education institutions (Shah, 2016), statistics that are almost double those of 2015 (Shah, 2015).

Given that they are high-quality courses with free option that reach unprecedented numbers of learners, MOOCs are considered to be a game-changer and powerful complement to higher education (Carver & Harrison, 2013; Jacoby, 2014; Ryan, 2013). The majority of MOOC learners are from the United States and Europe (Gillani & Eynon, 2014; Zhu, Sari, & Lee, 2018); these learners have high drop-out rates and low levels of commitment (Yang, Sinha, Adamson, & Rosé, 2013; Yuan, Powell, & Olivier, 2014). This has led researchers to doubt whether seeking formal recognition for coursework is even an objective for most MOOC learners (Kizilcec et al., 2013). Some researchers have expressed skepticism that enrollment in MOOCs is an indicator of learning intentions, suggesting that enrollment reveals a desire for entertainment or functions as a "shopping period" (DeBoer, Ho, Stump, & Breslow, 2014; Watson, Watson, Yu, Alamri, & Mueller, 2017). Research on MOOC interaction supports this viewpoint. A recent study found that a large proportion of learners who interacted on a particular discussion forum did not even attempt to submit assignments or pass exams to receive final grades (Gillani & Eynon, 2014). Unlike their counterparts in the Western world, 49% of MOOC learners in Colombia, the Philippines, and South Africa completed MOOCs with certificates, while another 30% of MOOC learners who did not receive certificates also completed MOOCs (Garrido, Koepke, Andersen, Mena, Macapagal, & Dalvit, 2016). The massive number of participants with diverse backgrounds and learning objectives makes MOOC interaction different from the interaction seen in other online courses.

Interaction via the MOOC platform primarily refers to the posts, comments, and responses on MOOCs' discussion forums (Bozkurt et al., 2016; Gillani, & Eynon, 2014; Hung, 2017; Pillutla, 2017; Schaffer, Huynh, O'Donovan, Hollerer, Xia, & Lin, 2016; Tawfik et al., 2017; Wu, Yao, Duan, Fan, & Qu, 2016; Zhang, Skryabin, & Song, 2016), which has long been considered a critical component of online learning (T. Anderson, 2004; Garrison & Cleveland-Innes, 2005; Wanstreet, 2006). A feature designed to promote learners' interaction, the discussion forum is used by popular MOOC providers in the global market, such as Coursera, edX, and Udacity. Indeed, by 2016, 48.3 million registered learners were interacting in discussion forums (Shah, 2016).

Although such interaction is not usually part of a course sequence or assigned credit (Seaton, Bergner, Chuang, Mitros, & Pritchard, 2014), instructors often consider discussion forums indispensable modules for their instructional design. Guàrdia, Maina, and Sangrà (2013) proposed ten design principles for MOOCs, four of which are related to learner-to-learner interaction. They argued that instructors should provide learners with clear netiquette information; activities; tasks; and tools for different types of interaction, such as discussion forums, social networking, peer assistance, and peer feedback (Guàrdia, Maina, & Sangrà, 2013). Beaven et al. (2014) encouraged MOOC learners to consider the amount of interaction and collaboration they require, since knowing this would allow the learners to adjust their levels of engagement to meet their needs and interests. Watson et al. (2016) introduced a “Share Your Story” forum designed for learners to share local and personal stories and start a global conversation. The instructors of this MOOC encouraged learners to share how the MOOC had impacted them, their family, and their community (Watson et al., 2016). Some MOOCs also encourage interaction among learners through compulsory peer-review tasks and debates in the MOOCs’ discussion forums and via other social networking services, such as Facebook, Twitter, Google+, and Google Hangouts (de Lima & Zorrilla, 2017).

Interaction has been shown to comprise a large portion of MOOC activities and to contribute to improved performance, higher satisfaction levels, and higher completion rates (Balakrishnan & Coetzee, 2013; Breslow et al., 2013; Gillani & Eynon, 2014; Kizilcec et al., 2013; Seaton, Bergner, Chuang, Mitros, & Pritchard, 2014; Woodgate, Macleod, Scott, & Haywood, 2015). According to a recent study, the learners enrolled in one of the first edX MOOCs, 6.002x: Circuits and Electronics, spent as much or more time interacting in the discussion forum as they did looking at videos, working on assignments, or taking quizzes, even though the forum was not mandatory (Seaton, Bergner, Chuang, Mitros, & Pritchard, 2014). Another Coursera-based MOOC, this time on business strategy, similarly emphasized interaction via a discussion forum (Gillani & Eynon, 2014). The percentage of learners who interacted in this particular discussion forum was 60% higher than the percentage of learners who received final scores, suggesting that many of the learners who actively interacted in the discussion forum did not even attempt to submit assignments or pass exams to receive final grades (Gillani & Eynon, 2014).

The content of this interaction can be analyzed using different frameworks depending on the research goals and context. For instance, the positive, neutral, or negative sentimental tone of MOOC interaction can be studied using sentiment analysis method. This method can identify linguistic classifiers that predict the sentimental tone of MOOC interaction (Balaji, Govindasamy,

& Akila, 2016; Wen, Yang, & Rose, 2014). The interaction is highly correlated with learners' satisfaction and completion rates (Lubis, Rosmansyah, & Supangkat, 2016); their typical opinions (Fong, 2017). The nature and level of interaction can be studied using the interaction analysis model (IAM) (Gunawardena et al., 1997). According to IAM, only the two lower phases of interaction in the analyzed MOOCs were observed; these observations revealed MOOC interaction to take place at relatively lower levels (Kellogg, Booth, & Oliver, 2014; Pillutla, 2017; Tawfik et al., 2017).

Interaction is an important component of MOOCs provided by all of the popular vendors, reaching at least 48.3 million learners (Shah, 2016). Interaction has been emphasized by researchers and instructors as a necessary component (Beaven et al., 2014; Guàrdia, Maina, & Sangrà, 2013; Watson et al., 2016) and embraced by high-performers and certificate-earners as an important learning activity (Breslow et al., 2013; Gillani & Eynon, 2014). Interaction has also been proven to be highly correlated with student satisfaction and completion rates (Balakrishnan & Coetzee, 2013; Breslow et al., 2013; Gillani & Eynon, 2014; Kizilcec et al., 2013; Seaton, Bergner, Chuang, Mitros, & Pritchard, 2014; Watson, Watson, Yu, Alamri, & Mueller, 2017; Woodgate, Macleod, Scott, & Haywood, 2015), making research on MOOC interaction a crucial undertaking to improve student satisfaction and completion rates.

Problem statement

While interaction on MOOCs has been studied from the perspective of quality and sentiment, two important factors--learners' backgrounds and social network positions-- have been understudied and they both are significant factors influencing interaction (Bayeck, Hristova, Jablokow, & Bonafini, 2018; Castaño-Muñoz, Kreijns, Kalz, & Punie, 2017; Swinnerton, Hotchkiss, & Morris, 2017).

Problem of research in background

Background information analyzed as part of MOOC research includes a learner's self-disclosed gender, year of birth, country of birth, current country of residence, race, level of education, current student, level of current program, subject area(s) of degree(s), employment status, industry of employment, English-language proficiency, other languages spoken, and state of residence (U.S.) (Bayeck, Hristova, Jablokow, & Bonafini, 2018; Gillani & Eynon, 2014; Swinnerton, Hotchkiss, & Morris, 2017). Differences in background tend to influence the interaction patterns of learners, thereby influencing student success. Older learners who work part-time or not at all are more likely to be commenters, and those who commented more tend to have better performance and lower dropout rate (Swinnerton, Hotchkiss, & Morris, 2017).

The majority of MOOC research uses easily obtainable descriptive statistics (Gasevic, Kovanovic, Joksimovic, & Siemens, 2014; Veletsianos & Shepherdson, 2016; Zhu, Sari, & Lee, 2018), such as absolute counts and proportion of learners with different age, location, highest degree, and/or employment status (Gillani & Eynon, 2014; Nesterko et al., 2013; Swinnerton, Hotchkiss, & Morris, 2017). Research on learners' backgrounds has usually focused on only one or a few of these characteristics, making it hard to see the larger picture. For example, Nesterko et al. (2013) compared the absolute counts of MOOC learners in different countries without discussing the statistical significance, finding that there was a higher number of certificate-earners among U.S. students. In one study, females tend to have negative attitudes towards interacting in single-gender groups, while younger learners don't have negative attitudes regardless of the gender (Bayeck, Hristova, Jablokow, & Bonafini, 2018). The results from prior research can sometimes even be contradictory. For instance, one study found that young adults from the Western world tend to interact more (Gillani & Eynon, 2014), while another demonstrated that older, part-time, and unemployed learners who have prior online experience interact more actively via the MOOC platform (Swinnerton, Hotchkiss, & Morris, 2017). In contrast, Breslow et al. (2013) found no relationship between age and achievement or between gender and achievement.

Problem of research in social network position

Social network position is the learner's position in the temporary MOOCs social network, it is measured by degree centrality, closeness centrality and betweenness centrality. Degree centrality is the number of edges a node has in a network; closeness centrality is the distance of an individual node in the network from all the other nodes; Betweenness Centrality is the number of shortest paths between any two nodes that pass via a given node (Freeman, 1978; Takaffoli, & Zaïane,2012; Wasserman, & Faust, 1994). Research studies on social network positions and MOOC interaction have tended to focus on macro-level interaction within an entire social network while overlooking the sub-populations or individuals involved. Even after determining the individual centrality of each learner, researchers have taken the average centrality of all learners and used it to represent the entire social network. For example, Tawfik (2017) used the average degree of nodes for each week of the discussion forum, without investigating each individual learner. This approach may cause researchers to neglect the fact that even 1% of MOOC learners constitute enough people to build a robust community with a noteworthy learning culture (Jackson, 2014).

This is also problematic since participation in MOOCs follows a long tail distribution since most learners tend toward disengagement (Jackson, 2014). The theory of the long tail was originally used in business to depict a large number of unique commodities, each with relatively low sales (C. Anderson, 2004). The long tail in business is thought to dominate the total sales profit of Internet-based e-commerce; a similar pattern has been observed in Web-based open education and MOOCs (Brown & Adler, 2008; Jackson, 2014). Although long-tail effects suggest that researchers should pay close attention to subpopulations and individuals, the majority of research to date focuses on high-frequency behaviors during interaction caused by the “head.” The interaction of subpopulations in the long tail could help instructors identify learners’ specific needs and provide customized support; however, this interaction has been understudied, with a focus on the entire social network.

Meanwhile, changes in social networking and interaction content have usually been discussed separately. Multiple studies only discussed one of these two important influencing factors (de Lima & Zorrilla, 2017; Gillani & Eynon, 2014; Schaffer, Huynh, O'Donovan, Hollerer, Xia, & Lin, 2016; Wu, Yao, Duan, Fan, & Qu, 2016). For example, Gillani and Eynon (2014) investigated when and with whom, but not with what content, learners tend to interact in a social network. Schaffer et al. (2016) used a social network graph to show that a large proportion (about 35%) of learners never receive replies to their original posts, and those who do receive replies are twice as likely to post again. However, they did not analyze the content of the posts and whether the content can predict the reply rate. Similarly, de Lima and Zorrilla (2017) depicted the tapering trend of social network density and identified the most popular nodes in the network without elaborating on the content of interaction among these nodes.

Even when they are discussed together, however, few measures have been taken to address the covariation of social network positions and the nature and depth of interaction (Bozkurt et al., 2016; Pillutla, 2017; Tawfik et al., 2017). For example, Bozkurt et al. (2016) sampled the most highly connected clusters in a MOOC discussion forum using social network analysis. They also identified different types of the interaction content; however, they did not address whether the identified clusters tended to have different types of interaction. Without considering the nature and depth of each node on a social network map, it is hard to make sense of the density of the nodes and active learners in a given network, since more frequent interaction does not necessarily mean that long, positive, and deep interaction is taking place.

Problem of methods

Survey is a popular measurement tool used in MOOC research to collect background data (Veletsianos & Shepherdson, 2016; Zhu, Sari, & Lee, 2018). Survey questions are designed by researchers or instructors, however, meaning that the questions are usually inconsistent across a range of MOOCs and depend on the researchers or instructors' interests and the MOOC subject. For example, learners may be asked questions about their prior knowledge and opinions of one specific MOOC in a survey (Hone & El Said, 2016). These questions are not always asked, meaning that the results are not easily transferable.

In contrast, information about learners' backgrounds and social network positions is easily collected via the MOOC platform. The most popular MOOC providers, Coursera, edX, and Udacity, ask learners to enter their background information when they sign up for the platform. The MOOC providers then store the information in their databases, allowing instructors to access this information if the learners register for their particular MOOCs. Popular social networking services like Facebook, Twitter, and Google+ also ask their users to enter demographic information, which can be obtained via Web crawlers if the users make it public (Wilson, Gosling, & Graham, 2012). Social network positions information is also easily collected via MOOCs database and Web crawlers as long as interaction occurs.

MOOC-related interaction occurs across different MOOC discussion forums, as well as on blogs and social networks like Facebook, Twitter, and Google+ (Cross & Whitelock, 2017; de Lima & Zorrilla, 2017; Harvey, Glinsky, Lowe, & Lowe, 2014; Wang, Anderson, Chen, & Barbera, 2017). For this reason, the conclusions drawn from learners' backgrounds and social network positions may be more readily transferable and important for the future design of MOOC interaction or interaction across other forms of social network learning.

In addition, it is hard to quantify the interaction that takes place on MOOCs' discussion forums. The massive, noisy, and incomplete raw data gathered from these forums may make the analysis of quantitative data, not to mention qualitative data, harder than usual. Identifying the predictive relationship among background information, social network position, and interaction would allows future MOOC researchers, instructors, and designers to speculate about the interaction patterns of learners.

The aforementioned studies have generally focused on either learners' backgrounds or social network positions. It remains unclear how background and social position together contribute to interaction. Although there is research on the contributions of background factors and social network positions to interaction, as mentioned above, the results are not sufficiently consistent and comprehensive to support instructor interventions and students' learning.

Importance of study

Interaction has long been considered a critical component of learning in traditional learning theoretical frameworks (Lave & Wenger, 1991; Leont'ev, 1978; Roschelle & Teasley, 1995; Vygotsky, 1978) and in online learning environments more specifically (T. Anderson, 2004; Garrison & Cleveland-Innes, 2005; Siemens, 2005; Stahl, Koschmann, & Suthers, 2006; Wanstreet, 2006). As an online learning platform first introduced in 2008, MOOCs have served unprecedented numbers of learners. This differentiates MOOC interaction from the interaction that takes place in traditional or other online learning environments. MOOCs have the potential to facilitate new knowledge and insight through the interaction of massive numbers of learners from around the world with unique life experiences and sociocultural contexts (Gillani & Eynon, 2014;

McAuley, Stewart, Siemens, & Cormier, 2010). Unlike their predecessors, which had smaller audiences, MOOCs present learner-to-learner interaction as the dominant form of interaction, while instructor-to-learner interaction is thought to be “nice but not expected” (Loizzo & Ertmer, 2016). The time MOOC learners spend on interacting in discussion forums is as much or even more than the time they spend looking at videos, working on assignments, or taking quizzes (Seaton, Bergner, Chuang, Mitros, & Pritchard, 2014), thereby suggesting a behavior pattern that is different than that seen on other platforms. In a 2014 study, a large proportion of learners who interacted on the discussion forum did not even attempt to submit assignments or pass exams to receive final grades (Gillani & Eynon, 2014). These unique characteristics of MOOC interaction merit investigation.

The MOOC learners who actively interact tend to have better performances and a higher completion rate than those who do not (Gillani & Eynon, 2014; Swinnerton, Hotchkiss, & Morris, 2017). However, compared to the number of learners enrolled, the number of learners who participate in interaction opportunities is extremely low (Breslow et al., 2013; Bruff, 2013; Gillani & Eynon, 2014; Manning & Sanders, 2013; University of Edinburgh, 2013). It has been argued that discussion forums are often plagued by information overload and chaos (Brinton et al., 2014; McGuire, 2013; Wise, Cui, Jin, & Vytasek, J., 2017). MOOC learners may perceive it as impossible to enter into a conversation with somebody about a particular aspect because of the massiveness of the discussion (Watson, Watson, Yu, Alamri, & Mueller, 2017), thereby leading to low levels of responsiveness (Huang, Dasgupta, Ghosh, Manning, & Sanders, 2014).

This study investigates the role of background factors and social network positions in interaction. The collection of background and social network position data via the MOOC platform is much easier than the data collection required for either sentiment analysis or the interaction analysis model. Given the relationship among background information, social network position, and interaction, the model investigated in this study makes it easier for instructors to spot the learners who interact with fewer words, negative sentiment, and/or superficial content and to intervene as necessary. This in turn allows instructors and teaching assistants to optimize their allocation of the limited time they have to spend while teaching massive numbers of learners. Previous research has indicated that a large proportion (about 35%) of MOOC students never receive replies to their original posts, and if they had received replies, they would have been twice as likely to post again and have lower chances of dropping out (Schaffer, Huynh, O'Donovan, Hollerer, Xia, & Lin, 2016). By investigating the effects of diversity of background information and social network position on interaction between learners, the model investigated in this study can recommend the learner's original post to the learners who have higher chance to give them rich, positive and deep interaction, thereby improving learning retention, experience, and performance. This personalized attention can be especially helpful for learners from developing countries who typically have less access to education, few local educational supports, and are highly motivated to earn certificates compared to their counterparts in development countries (Garrido, Koepke, Andersen, Mena, Macapagal, & Dalvit, 2016).

Summary of research questions

This study aims to find (a) at the individual level, the relationship among the learner's background, social network position, and interaction; and (b) at the group level, how the level of diversity among learners in a single group affected their interaction with one another. The two research questions guiding this study are:

1. From the perspective of the individual learner, how does one's background and social network position affect one's interaction?

2. From the perspective of learners interacting in threads, how does diversity in background and social network position contribute to the thread's interaction?

Definition of Terms

MOOCs is a new form of online learning emerging since 2008, when a 12-week Connectivism and Connective Knowledge (CCK08) by Stephen Downes and George Siemens. It is an widely accessible, high-quality, free online learning courses with massive number of learners created by top universities.

Interaction on MOOCs includes the post, comments and responses on MOOCs discussion forum and comments on peer-reviewed assignment.

Social Network Position is the learner's position in the temporary MOOCs social network, it is measured by degree centrality, closeness centrality and betweenness centrality. Degree centrality is the number of edges a node has in a network; closeness centrality is the distance of an individual node in the network from all the other nodes; Betweenness Centrality is the number of shortest paths between any two nodes that pass via a given node (Freeman, 1978; Takaffoli, & Zaïane,2012; Wasserman, & Faust, 1994).

Sentiment Analysis is the analysis approach to distinguish the positive, neutral, or negative sentimental tone (Balaji, Govindasamy, & Akila, 2016).

Interactive-Constructive-Active-Passive (ICAP) Model classifies learning activities into a taxonomy constructed with interactive, constructive, active and passive activities (Chi, 2009; Chi et al., 2018). Passive activities are defined as “being oriented toward and receiving information from the instructional materials without overtly doing anything else” (Chi et al., 2018, p.1786). Active activities are defined as the overt learning activities that can be observed. Constructive activities require learners to produce additional outputs not contained in the explicitly presented information. The learners would also be active while producing outputs, therefore constructive activities subsumes active activities. ICAP framework focuses on ‘dialoguing’ while prototyping interactive activities. The activities are classified to be interactive only while substantive dialoguing happened together with contribution from other learners.

Chapter 2

LITERATURE REVIEW

MOOCs

Massive open online courses (MOOCs) constitute an online learning platform with open, registerable online curricula and open-ended outcomes (McAuley, Stewart, Siemens, & Cormier, 2010). MOOCs are usually free online courses created by top institutions to serve massive numbers of learners (Liyanagunawardena, Adams, & Williams, 2013). MOOCs have been widely accepted as a form of online learning since 2008 when a the first MOOC was introduced (Deng & Benckendorff, 2017; Liyanagunawardena, Adams, & Williams, 2013; Uden, Sinclair, Tao, & Liberona, 2014). Stephen Downes (2008) distinguished between cMOOCs and xMOOCs. The prefix "c" stands for connectivist, while the prefix "x" stands for exponential. For example, CCK08 could be categorized as a cMOOC since it emphasized networked and discussion-based learning instead of considering instructors as the sole source of content (Deng & Benckendorff, 2017). xMOOCs usually follow the format used in traditional university settings, with highly structured curricula, clear learning objectives, video lectures, reading materials, assessments, discussion forums, live video sessions, and other activities. Each of these elements is thought to substitute for one element in traditional formal learning (Baturay, 2015; Deng & Benckendorff, 2017; Major & Blackmon, 2016). xMOOCs are usually provided by the most popular MOOCs providers such as Coursera, edX, and Udacity. The most popular MOOCs vendors have enabled 700 higher-education institutions to provide 6,850 MOOCs to 58 million learners by the end of 2016 (Shah, 2016), which is almost double the enrollment of 2015 (Shah, 2015).

Distance learning first appeared in 1728 when the Boston Gazette ran an advertisement for a distance stenography course (Kaplan & Haenlein, 2016; Phipps & Merisotis, 1999). It continued into the twentieth century supported by the invention of new media, such as radio and television (Phipps & Merisotis, 1999). However, researchers were skeptical of the impact of distance learning on higher-education institutions until the emergence of MOOCs (Liyanagunawardena, Adams, & Williams, 2013). Since a change in education could lead to a change in numerous related aspects of society and government (Pucciarelli & Kaplan, 2016), MOOCs may have wider influence than that which has been already observed in education (Kaplan & Haenlein, 2016).

MOOCs constitute the first learning platform that allows everyone free access as long as they have Internet service, while avoiding limiting the times and locations during which the courses are accessible (Ryan, 2013). Through MOOCs, learners can gain insight into a diverse range of ideas developed by unique individuals and in distinct cultures all over the world; learners can also plan for lifelong high-quality learning resources that are more easily accessible to them. MOOCs have affected different aspects of educational research, such as common pedagogical approaches, delivery methods, and business models (Jacoby, 2014).

MOOCs have also influenced an unprecedented number of people (Shah, 2015; 2016). Even 1% of MOOC learners have the potential to build robust communities with enough members to constitute learning cultures (Jackson, 2014). MOOCs enable learners from developing countries who have relatively lower educational levels to earn certificates, develop their professional skills, and further their careers (Garrido, Koepke, Andersen, Mena, Macapagal, & Dalvit, 2016). For more than 100 million children who cannot afford formal education, MOOCs can serve as a lifeline to rise above the poverty line (Conole, 2016), a goal that is otherwise nearly unreachable.

MOOCs and formal education

MOOCs are considered a game-changer and powerful competitor to formal education (Ryan, 2013). cMOOCs challenge traditional educational models and encourage innovation and new pedagogical practices in higher education (Yuan & Powell, 2013). xMOOCs mimic conventional higher-educational settings on a massive scale and democratize formal learning by breaking down traditional barriers such as cost and admission criteria (Dillahunt, Wang, & Teasley, 2014; Spector, 2014). MOOC learners from developing countries or those who are below the poverty line gain learning opportunities, professional skills, and career-building skills that are nearly impossible to achieve in traditional formal education (Conole, 2016; Garrido, Koepke, Andersen, Mena, Macapagal, & Dalvit, 2016).

However, the negative aspects of MOOCs such as their high drop-out rate and difficulties with retention, as well as the low commitment of Western learners, have drawn criticism (Nkuyubwatsi, 2014; Yuan, Powell, & Olivier, 2014). More specifically, these aspects of MOOCs have made researchers doubt whether seeking formal recognition is even among the goals of these sub-populations of MOOC learners (Kizilcec et al., 2013). Enrollment in MOOCs may not be an indicator of learning intentions in the same way that it is in traditional learning settings; in fact, enrollment may represent only a desire for entertainment or a "shopping period." The idea of a "shopping period" likens enrolling in different MOOCs before actually learning in one of them to entering different stores before purchasing a product (DeBoer, Ho, Stump, & Breslow, 2014; Watson, Watson, Yu, Alamri, & Mueller, 2017).

Instead of seeing MOOCs as either a game-changer or a poor substitute for formal education, some institutions have used MOOCs as a supplement by allowing students to take them as university-accredited courses (Cross & Whitelock, 2017; Cho & Byun, 2017). The American Council on Education (ACE) conducted research on applying its long-standing course-review and credit-recommendation service to MOOCs, thereby providing a credit pathway for certified MOOC learners (Sandeen, 2013).

2.1.3. Prior research on MOOCs

Liyanagunawardena et al. (2013) indicated that early MOOC studies (2008–2012) focused on eight different areas: (1) introductory, (2) concept, (3) case studies, (4) educational theory, (5) technology, (6) participant-focused, (7) provider-focused, and (8) other. The introductory studies introduce and explain different aspects of MOOCs; studies in concepts encompass discussion papers on topics such as the threats and opportunities that MOOCs present for higher education and its existing institutions, while case studies examine one or more MOOCs. Research on educational theory investigates the pedagogic approaches used, and technology-related research presents the software and hardware used. Finally, research on participants focuses on the backgrounds and behaviors of MOOC learners, while research on providers focuses on course creators and leaders (Liyanagunawardena, Adams, & Williams, 2013). Ebben and Murphy (2014) identified two key phases of MOOC research. From 2009–2011/2012, researchers focused on connectivist MOOCs, engagement, and creativity. They discussed the development of connectivism as a learning theory and considered technological experimentation and innovation in early cMOOCs. From 2012–2013, xMOOC researchers focused on learning analytics, assessment, and critical discourses about MOOCs. Themes of this phase include the rise of xMOOCs, the further development of MOOC pedagogies and platforms, the growth of learning analytics and assessment, and the emergence of a critical discourse about MOOCs (Ebben & Murphy, 2014).

The most frequently cited publications from 2013–2015 are generally student-focused, with commonly discussed topics including retention/dropout, peer assessment, participation and engagement (Veletsianos & Shepherdson, 2016). Research from 2014–2016 is also primarily student-focused, with other foci including design, context, impact, and instructors (Zhu, Sari, &

Lee, 2018). The most frequently discussed topics are those concerning MOOC participants or students, including participants' behaviors, motivation, satisfaction, performance, interaction, and retention. Students tend to have four motivations when enrolling in MOOCs: (1) to extend their knowledge, (2) to pursue their curiosity about MOOCs, (3) to challenge themselves personally, and (4) to obtain certificates (Hew & Cheung, 2014). Though a relatively small proportion of MOOC learners persist, perform well, and participate in interaction, those who do tend to have higher levels of satisfaction (Balakrishnan & Coetzee, 2013; Breslow et al., 2013; Gillani & Eynon, 2014; Kizilcec et al., 2013; Seaton, Bergner, Chuang, Mitros, & Pritchard, 2014; Watson, Watson, Yu, Alamri, & Mueller, 2017; Woodgate, Macleod, Scott, & Haywood, 2015).

Quantitative methods are the methods that are most commonly used in empirical studies, while descriptive analysis is the dominant data analysis method (Gasevic, Kovanovic, Joksimovic, & Siemens, 2014; Veletsianos & Shepherdson, 2016; Zhu, Sari, & Lee, 2018). Generally speaking, surveys, interviews, and log files are the most frequently adopted data-collection methods, with most researchers employing a single research method (Deng & Benckendorff, 2017; Zhu, Sari, & Lee, 2018). Each research area has its own preference regarding research methods. Student-focused research topics are investigated most frequently, usually using quantitative methods, while much of the design-focused, context-focused, and instructor-focused research uses qualitative research methods (Zhu, Sari, & Lee, 2018). Since the majority of MOOC research relies on easily obtainable descriptive statistics and content analyses, it is advocated to utilize in-depth learner and instructor interviews, focus groups, and actual MOOC session observations, as well as social network and thematic analyses, in future research (Zhu, Sari, & Lee, 2018).

Interaction

Interaction and learning

Contemporary learning theories consider interaction to be a critical learning component (Lave & Wenger, 1991; Leont'ev, 1978; Roschelle & Teasley, 1995; Vygotsky, 1978). Vygotsky (1978) proposed social development theory to emphasize the fundamental role of social interaction in cognitive development, positing that human learning has a specific social nature and process. Leont'ev (1978) also argued that a conscious, specifically human form of psyche emerges from social interaction. Lave and Wenger (1991) indicated that learning could not be constituted separately from the social world, and that "language use and, thus, meaning are situated in interested, intersubjectively negotiated social interaction." Roschelle and Teasley (1995) emphasized the effects of social interaction on the construction of shared knowledge in collaborative problem-solving. In addition to helping create the learning communities emphasized by the theories mentioned above, interaction allows for learner control, facilitates program adaptation, allows various forms of participation and communication, and aids in meaningful learning (Sims, 1999).

Interaction is defined as at least two objects and two actions that mutually influence one another (Wagner, 2001). In education, the objects are usually the learner, teacher, and content (T. Anderson, 2004). Interaction is beneficial for learning in general, but it is also beneficial for online learning more specifically (Conrad, 2014; Goodyear et al., 2014). One of the affordances of online learning is the profound and multifaceted increase that it promotes in learners' interaction capabilities (T. Anderson, 2004). Online interaction can minimize the constraints of space and time, thereby making learning more convenient (Reeves & Pedulla, 2011; Johnson & Johnson, 2008). Interaction in an online learning environment can also facilitate deeper engagement and knowledge convergence (Draper, 2015; Johnson & Johnson, 2008; Weinberger et al., 2007). Background factors such as student ability, gender, personality, and group composition on ability and gender all influence peer interaction (Webb, 1989).

Although interaction in online learning environments is not different from interaction in face-to-face environments in many respects, there are some prerequisites for effective online interaction because of its asynchrony. For instance, social interaction does not emerge automatically in asynchronous distributed learning groups (DLGs) that rely on computer-supported collaborative learning (CSCL) environments if the course facilitators are “taking for granted that participants will socially interact simply because the environment makes it possible and neglecting the social (psychological) dimension of the desired social interaction” (Kreijns, Kirschner, & Jochems, 2003, p 335). It is pointless for instructors to use an interactive medium if they do not structure and encourage interaction (Moore, 2001).

Interaction in MOOCs

Most of the research consider the posts, comments, and responses on MOOCs’ discussion forums as primary form of interaction via the MOOC platform (de Lima & Zorrilla, 2017; Dowell et al., 2015; Gillani & Eynon, 2014; Tawfik et al., 2017; Zhang, Skryabin, & Song, 2016). Other popular social network services such as Facebook, Twitter, Google+, and blogs also contribute to MOOC-related interaction (Cross & Whitelock, 2017; de Lima & Zorrilla, 2017; Wang, Anderson, Chen, & Barbera, 2017). As a new member of online learning, MOOC has served unprecedentedly massive numbers of learners (Shah, 2016) and facilitated the interaction among learners with unique life experiences and sociocultural contexts to build their knowledge and insight (McAuley, Stewart, Siemens, & Cormier, 2010; Gillani & Eynon, 2014). MOOCs learners primarily participated in learner-to-learner interaction, while considered instructor-to-learner interaction “nice but not expected” (Loizzo & Ertmer, 2016).

Student behaviors during the edX MOOC, 6.002x: Circuits and Electronics, were investigated using the parsing tracking logs method (Seaton, Bergner, Chuang, Mitros, & Pritchard, 2014). Seaton et al. (2014) found that interaction on discussion forums “account[s] for the highest rate of activity per student, with discussion activity increasing over the semester.” The time that MOOC learners spend interacting in discussion forums is as much or more than the time they spend looking at videos, working on assignments, or taking quizzes (Seaton, Bergner, Chuang, Mitros, & Pritchard, 2014). Gillani and Eynon (2014) observed the interaction of 4,337 participants, each of whom created at least one post or left one comment in the discussion forum of a Coursera-based MOOC on business strategy. They found that the percentage of learners who actively interacted via the discussion forum was 60% higher than the percentage of learners who received non-zero final scores, suggesting that a large number of forum users participated in the discussion without the intention of receiving final grades (Gillani & Eynon, 2014).

MOOC learners who do not participate in interaction have a higher dropout rate. As shown in a study of edX’s CS169.1x: Software as a Service course, learners who participated in the interaction on a weekly basis were very unlikely to drop out (consistently ranging from 4-7%), whereas those who never viewed the forum were very likely to drop out (37%) (Balakrishnan & Coetzee, 2013). Learners who simply viewed the interaction without posting or commenting also had a higher completion rate (Balakrishnan & Coetzee, 2013; Chiu & Hew, 2017).

High-performers and certificate-earners participate in MOOC forums more actively. In the aforementioned business strategy MOOC, over 20% of the forum participants earned 90% or higher, but only 2% of the total course participants reached this score level (Gillani & Eynon, 2014). The MOOC forum for 6.002x: Circuits and Electronics gathered 52% of certificate-earners but only 3% of all learners (Breslow et al., 2013).

However, there are also problems with the massive numbers of learners MOOCs serve. Compared to the number of learners enrolled, the number of learners interacted is very low (Breslow et al., 2013; Bruff, 2013; Gillani & Eynon, 2014; Manning & Sanders, 2013; University of Edinburgh, 2013). In at least 30% of MOOCs, new discussion threads are created at rates that are not feasible for students or teaching staff to digest (Brinton et al., 2014). Motivated by this contradiction in MOOC interaction, studies have discussed how factors such as background and social network position may influence interaction.

Analytical framework for interaction

The content of interaction via a MOOC platform has been investigated using different analytical frameworks. Some of the frameworks, such as the interaction analysis model (Gunawardena et al., 1997; Kellogg, Booth, & Oliver, 2014; Pillutla, 2017; Tawfik et al., 2017) and the connectivist interaction and engagement model (Wang, Anderson, Chen, & Barbera, 2017), aim to identify the nature and level of interaction. Others, such as sentiment analysis, focus on the emotional valence of interaction (Chaplot, Rhim, & Kim, 2015). Still others focus on linguistic features that are predictive of learning metrics of interest. These frameworks include discourse analysis (Dowell et al., 2015; Joksimović, et al., 2018), text mining, natural language processing, and computational linguistics (Crossley, McNamara, Baker, Wang, Paquette, Barnes, & Bergner, 2015; Robinson, Yeomans, Reich, Hulleman, & Gehlbach, 2016; Wise, Cui, Jin, & Vytasek, 2017). Finally, there are researchers who crowdsource their data analysis to categorize speech acts via MOOC forums (Arguello & Shaffer, 2015).

Content analysis

The interaction analysis model is a model that categorizes learner-to-learner interaction into five distinct phases: Phase I, during which learners share or compare information; Phase II, during which learners discover and explore dissonance or inconsistency; Phase III, during which learners negotiate meanings and co-construct knowledge; Phase IV, during which learners test and modify their knowledge; and Phase V, during which learners agree on and apply their knowledge. All five phases have sub-phases. The phases are progressive, meaning that each subsequent phase represents a deeper level in the social construction of knowledge (Gunawardena et al., 1997). This model has been applied in the analysis of learner-to-learner interaction, showing that the majority of interaction via MOOC platforms tends to stop at Phase I or Phase II (Tawfik et al., 2017).

The connectivist interaction and engagement model is designed to help researchers analyze the interaction taking place via a cMOOC (Wang, Anderson, Chen, & Barbera, 2017). This framework includes innovation interactions, sensemaking interactions, wayfinding interactions, and operation interactions. The four levels of interaction via a cMOOC platform constitute a network with significant recursion. Lower levels of interaction tend to be seen in the early phases of a course.

Sentiment analysis

Sentiment analysis uses accurate sentiment classifiers to determine the positive, negative, and objective sentiments of interactions with a specificity factor (Balaji, Govindasamy, & Akila, 2016). Wen, Yang, and Rose (2014) utilized sentiment analysis to study drop-out behavior and observed a significant correlation between the sentiments expressed during the discussion forum interaction and the number of students who dropped the course. Positive classifiers include “incredibly,” “benefits,” “enjoyment,” “richer,” and “guarantee,” among others, while negative classifiers include “missed”, “negative”, “low-rated”, “taxing”, “superficial”, “breaking, worry”, among others. These classifiers can help researchers to distinguish among different sentiments about courses, lectures, assignments, and peer assessment (Wen, Yang, and Rose, 2014).

Lubis, Rosmansyah, and Supangkat (2016) analyzed learning reviews using sentiment analysis in order to predict learning satisfaction. They found that learners who left positive reviews had higher satisfaction and completion rates. Fong (2017) analyzed the comments on MOOC-related news using sentiment analysis and found four typical perspectives, which are those of potentialists, numerics, detractors, and watchers. Potentialists hold positive attitudes towards MOOCs and enjoy advocating for them; numerics hold neutral attitudes and analyze the amount of money and time spent by MOOC facilitators or learners; detractors leave comments with negative sentimental tones, suggesting that they are unconvinced of the merits of MOOCs; and finally, watchers appear to have neutral sentiments and only ask questions about MOOCs and their potential impact on students in higher education (Fong, 2017). Sentiment analysis of Twitter data has been used to discover participants’ perceptions of MOOC learning (Shen & Kuo, 2015). Shen and Kuo (2015) found that most MOOC-related tweets were neutral, and half of the retweets that were not neutral came from the top 10% of influencers.

Linguistics analysis

Researchers who are not satisfied with predicting student achievement using simple demographic benchmarks started to consider linguistic analysis as an alternative. Linguistics analysis can help qualitative researchers analyze the content of interaction automatically via text mining packages, which may result in massive time savings for the researchers. Linguistics analysis offers another advantage that qualitative analysis of MOOC interaction cannot provide: linguistic features can be used for predicting metrics of interest. For example, linguistics analysis can help researchers extract those linguistic features from open-ended survey questions or discussion forum interactions that lead to learners' successful class completion, thereby predicting student achievement (Crossley, McNamara, Baker, Wang, Paquette, Barnes, & Bergner, 2015; Wise, Cui, Jin, & Vytasek, 2017).

Linguistics analysis can also be applied to the classification of pre-labelled discussion forum data with reasonably precise and transferable results; for example, it can be used to identify linguistic features that can predict whether an interaction between learners is content-related (Wise, Cui, Jin, & Vytasek, 2017). It can also classify the phase of interaction on basis of interaction analysis model with a 80% precision (Pillutla, 2017). This can save MOOC facilitators a considerable amount of time by helping them to avoid screening irrelevant information. Linguistics analysis can also remind, monitor, and summarize the writing assignment to scaffold reflection writing (Fan, 2017). Therefore, this analysis approach is suitable for research that investigated the content of massive amount of interaction such as the current research. Therefore, this analytical approach is suitable for research that investigates the content of a massive amount of interaction such as the current research.

Effects of Background on MOOC Interaction

The background information collected from the MOOC database or through pre-surveys has been primarily considered using descriptive analysis (Gasevic, Kovanovic, Joksimovic, & Siemens, 2014; Veletsianos & Shepherdson, 2016; Zhu, Sari, & Lee, 2018). The effects of background information such as gender, region, and age on learners' preferences for interaction have been investigated (Bayeck, Hristova, Jablokow, & Bonafini, 2018; Castaño-Muñoz, Kreijns, Kalz, & Punie, 2017; Swinnerton, Hotchkiss, & Morris, 2017). Education level, employment status, and prior online experience have also been considered (Castaño-Muñoz, Kreijns, Kalz, & Punie, 2017; Swinnerton, Hotchkiss, & Morris, 2017), as has proficiency in English (Cho & Byun, 2017).

Differences in learners' backgrounds tend to influence the learners' interaction patterns and thereby their success (Swinnerton, Hotchkiss, & Morris, 2017). Females tend to have negative attitudes towards interacting in single-gender groups, while younger learners cared less regardless the gender (Bayeck, Hristova, Jablokow, & Bonafini, 2018). One study found that young adults from the Western world tend to interact more (Gillani & Eynon, 2014), while another demonstrated that older, part-time, or unemployed learners who have prior online experience interact more actively via the MOOC platform (Swinnerton, Hotchkiss, & Morris, 2017).

Employed learners who have support from their employers spend significantly more time interacting compared to learners who lack support (Castaño-Muñoz, Kreijns, Kalz, & Punie, 2017). Interaction skills and information skills are positively related to online interaction (Castaño-Muñoz, Kreijns, Kalz, & Punie, 2017). Learners' locations and levels of proficiency in English also influence the frequency of and learners' preference for interaction. European and North American participants interact more actively on forums than those from Asia and interact in online forums more actively (Gillani & Eynon, 2014), while non-native speakers are less interactive online and prefer to have face-to-face interaction (Cho & Byun, 2017). The relationship between interaction and other motivational factors such as intentions to finish and tuition have also been examined (Cross & Whitelock, 2017).

The results of the research on the effects of background on interaction are often descriptive and partial, and they are sometimes even contradictory. The effects of factors in researcher-designed pre-surveys is encouraging; since the pre-surveys of different MOOCs are not the same, however, the results are not easily transferable or applicable to future studies' design. A more in-depth and transferable method of analysis would require that background information be collected across different MOOCs, MOOC vendors, or even other social network platforms that support MOOCs.

Social Network Analysis

Social network analysis, sometimes referred to as "structural analysis" (Wellman & Berkowitz, 1988), originated from "sociometry," a technique for eliciting and graphically representing individuals' subjective feelings toward one another (Moreno, 1934). Sociometry was not widely recognized as a field of research until Harrison C. White, together with his students, embraced a standard paradigm (Freeman, 2004, p. 127). In the social sciences, sociometry is used to investigate social structures using networks and graphic theory (Otte & Rousseau, 2002). Although social network research has been criticized as lacking a (native) theoretical framework and instead being "merely descriptive" or "just methodology" (Borgatti, Mehra, Brass, & Labianca, 2009), there are in fact three theoretical approaches that have influenced social network research. These are the two-step flow of communication hypothesis, the theory of weak ties, and diffusion of innovations (Liu, Sidhu, Beacom, & Valente, 2017). Two-step flow hypothesis argues the mass media initially influences opinion leaders, who then influence their their social contacts in the social network (Lazarsfeld, Berelson & Caudet, 1944). The theory of weak ties emphasizes the role of weak social ties in diffusing information (Granovetter, 1983). The diffusion of innovations theory is introduced as the process in which innovation is diffused among members through certain social system (Rogers, 2010).

The key concepts that have been used to organize research on network effects are centrality, cohesion, and structural equivalence (Liu, Sidhu, Beacom, & Valente, 2017). Degree centrality, closeness centrality, and betweenness centrality are popular measures for assessing structural centrality (Freeman, 1979). Degree centrality refers to the number of edges a node in a network has. Nodes with high degree centrality have more social ties for receiving and disseminating information than do nodes with low degree centrality (see Figure 1, black node). Betweenness centrality refers to the number of shortest paths between any two nodes that pass a given node. Nodes with high betweenness centrality are more likely than other nodes to serve as bridges in the network (see Figure 1, light grey node). Finally, closeness centrality is the distance of a node in the network from all of the other nodes. Individuals with higher closeness centrality can reach all of the other individuals in the network with fewer steps (see Figure 1, dark grey node) (Freeman, 1978; Liu, Sidhu, Beacom, & Valente, 2017; Takaffoli & Zaïane, 2012; Wasserman & Faust, 1994).

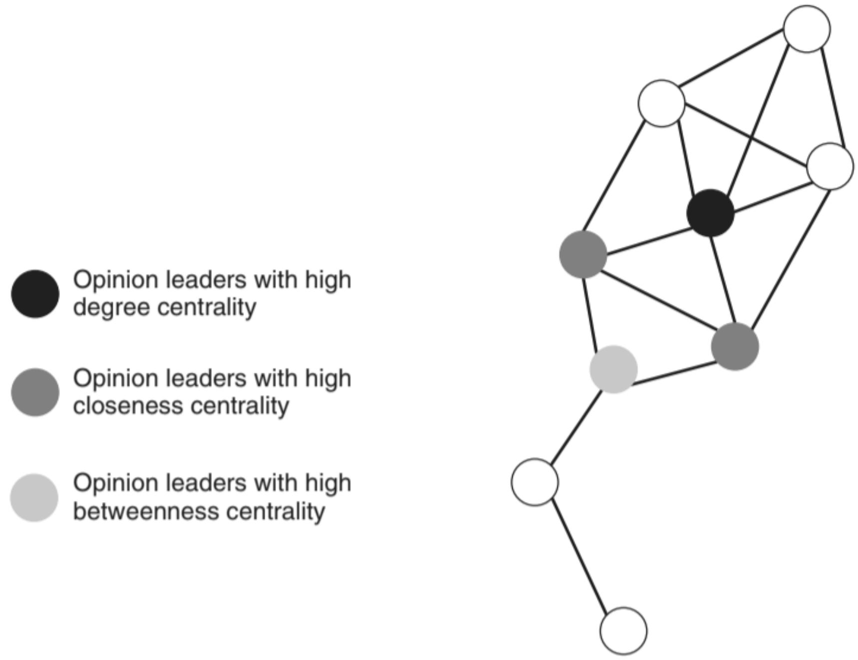

Figure 1. Network illustration of opinion leaders with high degree centrality, closeness centrality, and betweenness centrality (Liu, Sidhu, Beacom, & Valente, 2017).

Cohesion can be measured by determining the number of exchanges between individuals, the geodesic distance between individuals, or the minimum number of cut-points necessary to disconnect individuals (Reffay & Chanier, 2003). Another popular measurement of cohesion is density, which is “the number of lines in a simple network, expressed as a proportion of the maximum possible number of lines” (De Nooy, Mrvar, & Batagelj, 2011, p. 63).

Structural equivalence is used to identify network positions that have similar patterns of connections with the rest of the network (Burt, 1987). Actors that occupy structurally equivalent positions often have similar characteristics (Liu, Sidhu, Beacom, & Valente, 2017). Social network analysis has been widely applied in networked learning and computer-supported collaborative learning (CSCL) to answer questions about participatory patterns and changes over time that cannot be fully addressed by content analysis, interviews, observations, or questionnaires (De Laat, Lally, Lipponen, & Simons, 2007).

Many meaningful conclusions about group interaction, communication, and dynamics have been drawn from social network analysis. For example, Haythornthwaite (2001) performed social network analysis of a computer-supported collaborative learning environment to detect the developing trend of learner-to-learner interaction and the cohesive teams in which members interacted intensively over time.

The cohesion of a network is positively affected by a teacher's presence. Interaction participated in or facilitated by teachers can generate more threads compared to others (Martinez, Dimitriadis, Rubia, Gomez, & de la Fuente, 2003). The cohesion found using social network analysis can be useful for identifying isolated participants, active subgroups, and the various roles of the participants who interact in collaborative distance learning (Cho, Stefano, & Gay, 2002; Daradoumis, Martinez-Mones, & Xhafa, 2004; Reffay & Chanier, 2003).

Social network analysis has also been used to investigate the knowledge-building and acquisition during interaction in collaborative learning environment. The active user pairs and the documents they shared were identified to gain a richer understanding of the knowledge-building procedure. It was found that tutors did not play an important role in this CSCL environment (Nurmela et al., 1999). The recommendations made by highly "central" actors have been found to exert more influence on participants on a discussion board than those made by peripheral actors (Cho, Stefano, & Gay, 2002; Fitzgerald & Paukszt at, 2003).

Effects of Social Network Position on MOOC Interaction.

Compared to the constant and intrinsic aspects of learners' backgrounds, such as age, gender, level of education, and location, learners' social network positions are rather temporary. Research focusing on social networks has highlighted the actors (nodes) and ties (edges) of interaction while overlooking the content of interaction. One of the most widely used analysis frameworks is social network analysis (SNA). Social network analysis usually visualizes a social network through social maps and quantifies the positions of learners through connection, distribution, and segmentation. It considers each learner who has created at least one post or comment in a discussion thread as a node; the connections between two learners if they have co-posted in at least one discussion thread are known as edges (Dowell et al., 2015). Many studies have used social network analysis to predict metrics of interest (Hung, 2017; Schaffer, Huynh, O'Donovan, Hollerer, Xia, & Lin, 2016) or to depict the statuses of social networks across sub-forums or time by visualization or social network metrics (Bozkurt et al., 2016; Gillani & Eynon, 2014; Pillutla, 2017; Tawfik et al., 2017; Wu, Yao, Duan, Fan, & Qu, 2016).

Two trends have been discovered via social network analyses of MOOC interaction. First, the MOOC discussion forum is an optional, open, and loosely structured environment (Gillani & Eynon, 2014; Zhang, Skryabin, & Song, 2016), meaning that the relationships among members of the social network are usually transient and unlikely to continue after the MOOC is finished (de Lima & Zorrilla, 2017). Moreover, the density of the social network tends to decrease and segment over time (de Lima & Zorrilla, 2017; Gillani & Eynon, 2014; Schaffer, Huynh, O’Donovan, Hollerer, Xia, & Lin, 2016; Wu, Yao, Duan, Fan, & Qu, 2016; Zhang, Skryabin, & Song, 2016). A large proportion of students never receive replies to their original posts, and those who do receive replies are twice as likely to post again and have lower chances of dropping out (Schaffer, Huynh, O’Donovan, Hollerer, Xia, & Lin, 2016).

Second, there is often a group of participants who interact as central nodes (Gillani & Eynon, 2014; Goggins, Galyen, Petakovic, & Laffey, 2016; Tawfik et al., 2017). These central nodes have a better chance of being high performers, but they do not exclusively interact with other high performers (Gillani & Eynon, 2014). A large proportion of the information is disseminated by the central nodes, and their suggestions are more easily accepted by other learners (Shen & Kuo, 2015). Instructors can be central nodes in traditional instructional settings (Martinez, Dimitriadis, Rubia, Gomez, & de la Fuente, 2003), but in MOOC discussion forums, they do not play a central role in the interaction (de Lima & Zorrilla, 2017; Gillani & Eynon, 2014; Loizzo & Ertmer, 2016; Schaffer, Huynh, O'Donovan, Hollerer, Xia, & Lin, 2016; Wu, Yao, Duan, Fan, & Qu, 2016). The position of instructors is more peripheral when they facilitate interaction out of MOOC discussion forums via other social networking services (de Lima & Zorrilla, 2017).

In general, social network analysis focused on the macro level. However, individual learners especially central nodes played important role in the interaction and information dissemination, which implied former research using social network analysis could have neglected rich individual information. In the current study, the social network position will be analyzed at the individual level to address this problem.

Summary

Although the effects of learners' backgrounds and social network positions on interaction have been discussed in relation to the MOOC platform, they have not been addressed simultaneously in order to demonstrate the relative strength of effects on interaction. Future studies would benefit from research that sheds light on whether learners' long-term intrinsic background traits or temporary social network positions have greater influence on the learners' interaction patterns on discussion forums.

Chapter 3

METHODOLOGY

Participants

The participants in this study are learners who were enrolled in the MOOC entitled Creativity, Innovation and Change (CIC) offered at The Pennsylvania State University in 2013. This MOOC has served over 200,000 learners from more than 190 countries in 2013 and 2014. It included several peer-reviewed assessment projects in its compulsory course sequence, which constituted a second type of interaction in addition to the discussion forum. It also had a parallel Chinese version, which could potentially serve 1.2 billion native Chinese speakers. This study used the data from English discussion forum, where the MOOC learners chose to speak English.

The data collected from the CIC MOOC platform include demographic information about the learners, a pre-survey and post-survey, the full-text record of the learners' interaction on the discussion forum, and the peer/mentor-reviewed assignments. The demographic information includes each learner's self-disclosed gender, year of birth, country of birth, current country of residence, race, level of education, current student, level of current program, subject area(s) of degree(s), employment status, industry of employment, English-language proficiency, other languages spoken, and state of residence (U.S.).The pre-survey and post-survey questions can be seen in Appendix. The forum posts, comments, and threads and assignment submissions are all time-stamped.

Research Context

The research context for this study is a six-week MOOC offered by Penn State via Coursera and entitled Creativity Innovation and Change. Each week, the MOOC learners were asked to watch videos, participate in the online discussions, submit assignments, and evaluate other students' assignments. The online discussion forum had eight sub-forums, general discussions, a meet-and-greet, and one sub-forum for each week. There were no mandatory readings or quizzes. The primary topics covered in this MOOC can be seen in Table 1.

Table 1. The Topics and Assignments of Creativity, Innovation and Change.

Week	Topics	Peer-graded Assignments
1	Welcome to CIC!	NA
2	CIC Mindset and Innovation Toolbox.	1. Failure Resume 2. Shoe Tower
3	Understand Creative Diversity.	1. Creativity Style Estimation 2. Idea Generation Techniques 3. Paradox of Structure 4. Creative Diversity
4	CENTER Model.	1. Excellence/Measuring Your Creative Output 2. Life Ring
5	Value Creation.	1. Change Equation 2. Social Entrepreneurship 3. Action Map
6	Change.	1. Action Plan 2. Field Trip

Research Questions

This study centers on two goals: (a) to find, at the individual level, the relationship among the each learner's background, social network position, and interaction; and (b) to find, at the thread level, how the level of diversity among learners in a single thread affected their interaction with one another. Diversity in background and social network position are measured via the variance of learners in each thread. The research questions guiding this study are:

1. From the perspective of the individual learner, how does one's background and social network position affect one's interaction?
2. From the perspective of learners interacting in threads, how does diversity in background and social network position contribute to the thread's interaction?

The length and sentimental tone will be analyzed through the text mining package textblob 0.15.1, the specific process is presented in chapter 4 with examples of results. The social network position will be analyzed using network analysis package NetworkX 2.3. The level of interaction will be measured using the interaction analysis model (ICAP), which has been applied to MOOC interaction analysis in other studies (Gunawardena et al., 1997; Kellogg, Booth, & Oliver, 2014; Pillutla, 2017; Tawfik et al., 2017). The details of ICAP analysis are specified in the section 3.4.2. These measurements of interaction reflect both the quantity (length) and the quality (sentiment and level) of interaction.

The level of diversity will be conceptualized as the variance in each metric of learners who interacted with each other, which is specified in chapter 4 with examples of results. Passive activities are those that are "oriented toward and receiving information from the instructional materials without overtly doing anything else" (Chi et al., 2018, p. 1786). This study focused on an online discussion forum and passive activities cannot be observed, therefore, only Active-Constructive-Interactive (hereinafter referred to as ACI) levels were used.

Procedure

Data subsetting

The Penn State MOOC, Creativity, Innovation, and Change (CIC) encourages the students to share and discuss course materials, projects and other course-related topics through the discussion forum. The 2013 CIC MOOC had 17019 enrolled students who answered at least one demographic information question. The discussion forum recorded 5247 unique threads, 7155 unique learners who posted or commented for at least one time, and 26325 unique posts and comments. Since this study focuses on the relationship between the demographic information, social network position, and discussion forum interaction, posts and comments from users who did not submit their demographic information are not included in the analysis.

The posts and comments came from 104 sub-forums. This study focused on learner-to-learner interaction, therefore all instructor posts and comments were removed. Threads with less than 2 posts and less than 5 views were considered to be inactive and were removed. Similarly, sub-forums with less than 10 posts or comments were considered to be inactive and were removed unless they were among the 9 content-related sub-forums that invited active discussion of lecture videos (Week 3 Lecture Video, Week 4 Lecture Videos, Week 4 Articles and Videos, Week 5 Lecture Videos, Week 5 Exercises, Week 6 Exercises, Week 7 Exercises, Week 7 Articles and Videos, Week 8 Lecture Videos, Week 8 Articles and Videos). After removing the aforementioned threads and forums, 5705 posts and comments created by 875 learners remained for analysis.

The text in the posts and comments was also pre-processed to remove non English strings. Each post or comment was compared to the English words lexicon from a widely used natural language processing library natural language toolkit (NLTK). If the number of English words was less than 50%, the post or comment was considered to be non-English and removed from the dataset.

This study focuses on the interaction that took place via the CIC MOOC discussion forum, meaning that the raw data of learners who never posted or responded to the discussion forum was removed. The raw data from these learners may be noisy and incomplete; for example, it is possible that there are missing values in background indicators such as highest degree and employment status. Such missing values could affect the auto-classification process introduced later in section 3.4.3. Therefore, the missing values were also removed. 195 posts or comments were removed via this elimination process. Since this study focused on the interaction among learners, the 99 learners who posted but never received a reply were removed for further analysis. The final dataset used in this study contains 5510 posts or comments from 730 learners.

Content analysis

Two content analysis models were compared to find the better one to serve for the research goal of this study. They all have hierarchical levels (Chi, 2009; Gunawardena et al., 1997) and have been used in the content analysis of MOOC discussion forum (Tawfik et al., 2017; Wang, Yang, Wen, Koedinger, & Rosé, 2005).

Interaction Analysis Model (IAM)

The interaction analysis model (Gunawardena et al., 1997) is a method of qualitative analysis that requires coding by researchers. This is hard to apply to the massive numbers of learners in MOOCs; in this study, therefore, natural language processing will be applied to classify each of the study's phases. Thirty percent of the interaction threads from each of the eight subforums of the overarching CIC MOOC discussion forum will be randomly sampled, with one original post or comment sampled from each thread selected in the last step. Stratified random sampling will be used since previous research has found that interaction patterns change across weekly sub-forums over time (Gillani & Eynon, 2014).

Interaction analysis will be conducted in order to classify the dataset into different phases. First, the researcher will use the interaction analysis model (Table 2) to pre-label each data point with one of the five phases.

Table 2. Interaction Analysis Model (IAM) (Gunawardena et al., 1997).

PHASE I: Sharing/Comparing of Information	
A. A statement of observation or opinion B. A statement of agreement from one or more other participants C. Corroborating examples provide by one or more other participants D. Ask and answering questions to clarifying details of statement E. Definition, description or identification of a problem	[PhI/A] [PhI/B] [PhI/C] [PhI/D] [PhI/E]
PHASE II: The Discovery and Exploration of Dissonance or Inconsistency Among Ideas, Concepts or Statements.	
A. Identifying and stating the areas of disagreement B. Ask and answering questions to clarify the source and extent of disagreement C. Restate the participant's position and probably advancing the argument and consideration in its support by references to the participant's experience, literature, formal data collected, or proposal of relevant metaphor or analogy to illustrate point of view	[PhII/A] [PhII/B] [PhII/C]
PHASE III: Negotiation of meaning/Co-construction of knowledge	
A. Negotiation or clarification of the meaning of terms B. Negotiation of the relative weight to be assigned to types of argument C. Identification of areas of agreement or overlap among conflicting concepts	[PhIII/A] [PhIII/B] [PhIII/C] [PhIII/D]

D. Proposal and negotiation of new statements embodying compromise co-construction E. Proposal of integrating or accommodating metaphors or analogies	[PhIII/E]
PHASE IV: Test and Modification of Proposed Synthesis or Co-construction	
A. Testing the proposed synthesis against "received fact" as shared by the participants and/or their culture B. Testing against existing cognitive schema C. Testing against personal experience D. Testing against formal data collected E. Testing against contradictory testimony in the literature	[PhIV/A] [PhIV/B] [PhIV/C] [PhIV/D] [PhIV/E]
PHASE V: Agree Statement/Application of Newly Constructed Meanings	
A. Summarization of agreement(s) B. Applications of new knowledge C. Metacognitive statements by the participants illustrating their understanding that their knowledge or ways of thinking (cognitive schema) have changed as a result of the conference interaction	[PhV/A] [PhV/B] [PhV/C]

The IAM model is used to analyze a randomly selected sample. The distribution of its levels can be seen in the Figure 2. It is obvious that the distribution is very skewed, most of the posts or comments are classified as phase 1, sub phase A: a statement of observation or opinion.

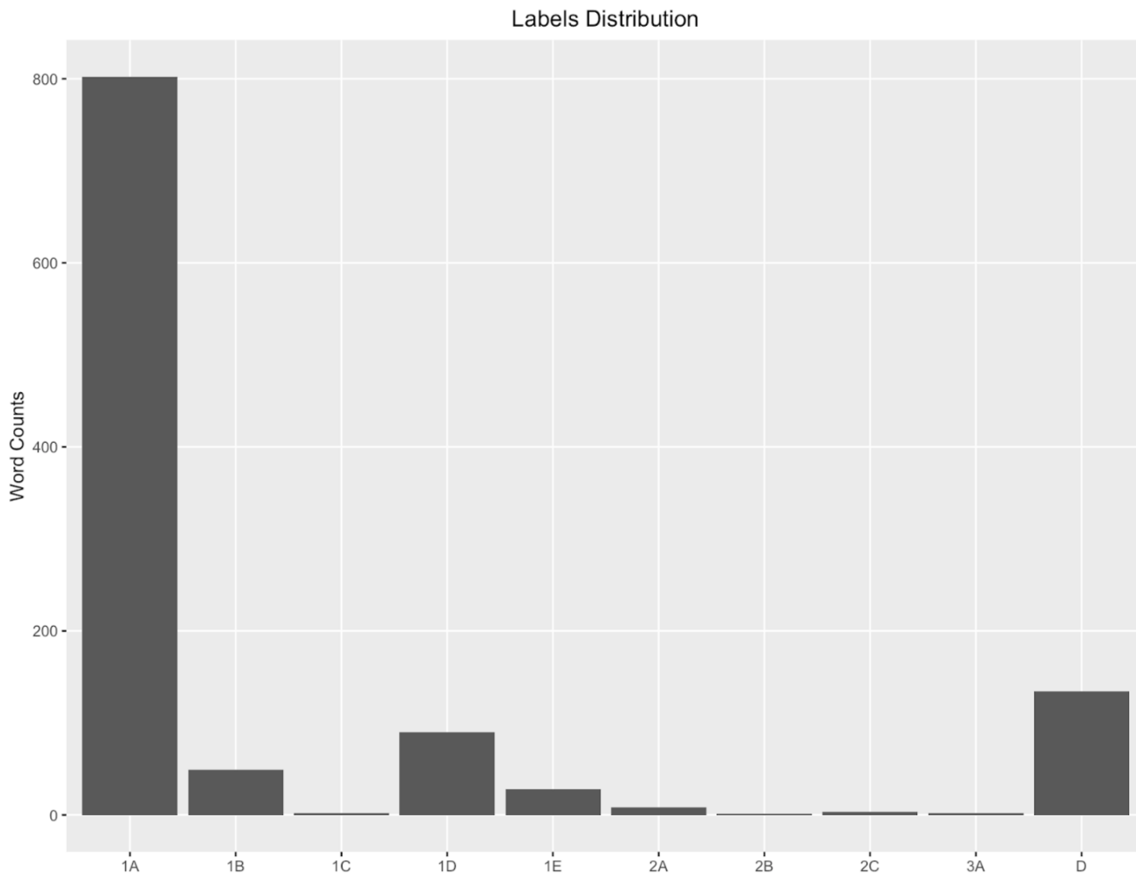

Figure 2. Distribution of IAM Model Levels.

Interactive-Constructive-Active-Passive (ICAP) model

The Interactive-Constructive-Active-Passive (ICAP) framework (Chi, 2009) has been used to evaluate the interaction level of MOOC discussion forum posts and comments and to automatically classify interactions via machine learning algorithms (Wang et al., 2005). ICAP classifies learning activities into a taxonomy of interactive, constructive, active, and passive activities. Passive activities are those that are “oriented toward and receiving information from the instructional materials without overtly doing anything else” (Chi et al., 2018, p. 1786). As long as overt activity is observed, the learning activities are considered to be active. Constructive activities require learners to produce additional outputs not explicitly contained in the presented information. The learners are active while producing outputs; therefore, constructive activities subsume active activities. The ICAP framework focuses on ‘dialoguing’ (Chi, 2009) while prototyping interactive activities. Activities are classified as interactive only when substantive dialoguing happens alongside contributions from other learners.

Table 3. The Coding Scheme Based on ICAP Model

Active Activities	
Chi’s Definition	Doing something physically.
Criteria	1. The post/comment does not contain any original outputs go beyond the presented information. 2. There is merely social, factual or evidential information presented by activating the preexisting knowledge without further modification. 3. It doesn’t matter if the learner is talking to a counterpart.
Example	1. This is a very interesting thread. I am also an artist, but am focusing on a different project for this course. I like your ideas (both of you) very much. a. This is a very interesting thread.”**-- social, no original output.** b. “ I am also an artist, but am focusing on a different project for this course.” **-- fact, no original output.** c. “I like your ideas (both of you) very much.” -- social, no original output. 2. Yes I like your creative process of thinking. The paper airplane makes so much sense. Great idea. **-- social, no original output.**
Constructive Activities	
Chi’s Definition	Producing outputs that contain ideas go beyond the presented information
Criteria	1. Overt outputs that go beyond the presented information can be observed. 2. Evidence can be found to prove that the outputs involve the learner’s construction 3. Evidence of reasoning and/or reflection/idea-justification is clear in the post

Example	1. No think about what a pop song takes people, ideas and the knowledge of notes. The team is people, knowledge of practice. Each creative style each person has to create a whole instead of parts. a. **construct an opinion "**Each creative style each person has to create a whole instead of parts." **with** "pop song" **example** 2. Hi Amy ;o)I wonder if sometimes it's less to do with lack of interest and more to do with "what if I don't get it". . Hi Amy **-- social, but no evidence can be found to prove the follow-up statement is built on what Amy presented, so not interactive** a. I wonder if sometimes it's less to do with lack of interest and more to do with "what if I don't get it". -- **constructing an opinion**
Interactive Activities	
Chi's Definition	Dialoguing substantively on same topic, not ignoring the partner's contribution.
Criteria	1. Constructive 2. Talking to a specific counterpart 3. Evidence can be found to prove the counterpart contribute to the construction 4. Evidence that the poster is expanding and building with reasoning/justification on a prior question
Example	1. Hi Janet - sounds like you've a couple of different although similar businesses. That could make you even busier! Do you find the two businesses complement each other or are they separate? Have you developed some of your employees so that they can relieve you of some day to day tasks. That could have a significant effect on how much time you have available for the other things in your life. I think that its important to be aware of all the resources that are available to you for all your 'projects'. I have found that doing some of the exercises on this course have helped me to understand this better and to actually get a better understanding of what resources I've got access to. a. Hi Janet **-- a counterpart** b. sounds like you've a couple of different although similar businesses. **-- contribution of a counterpart** c. Do you find the two businesses complement each other or are they separate? Have you developed some of your employees so that they can relieve you of some day to day tasks. That could have a significant effect on how much time you have available for the other things in your life. I think that its important to be aware of all the resources that are available to you for all your 'projects'. -- use inquiries to **construct suggestions** d. I have found that doing some of the exercises on this course have helped me to understand this better and to actually get a better understanding of what resources I've got access to. -- **constructing an opinion** 2. You could start off with the services in the library. Once you've got the momentum going and its proven to be sustainable you can design a

	delivery package and start selling it.. assuming you can do that? Can you do that?? Or even consultancy. . You **-- a counterpart** a. Once you've got the momentum going and its proven to be sustainable you can design a delivery package and start selling it.. assuming you can do that? Can you do that?? Or even consultancy. **-- construct** a suggestion based on the counterpart's situation/**contribution**

In this study, a learner was considered to be active if he/she added a post/comment to the discussion forum providing factual or evidential information that required the activation of existing, unmodified knowledge. In such a case, no original outputs beyond the existing information are generated. If a learner produced outputs that went beyond the presented information and allowed the learner to engage with new ideas, develop insight, or make conclusions, it was considered a constructive activity. An interactive activity involves producing outputs on basis of contributions from other learners. The contributions from others should "provide additional information, a new perspective, corrective feedback and a new path or line of reasoning to pursue" (Chi, 2009, p. 87). Since this study analyzed online learning discussion forum posts, passive activities, which cannot be observed, were not included in the analytical framework. The ICAP is a hierarchical framework in which being interactive is considered to engage higher cognitive processes than being constructive and being constructive is considered to engage higher cognitive processes than being active. If the sentences of a post/comment are classified into different categories, the post belongs to the highest category. The coding scheme can be seen in table 3.

The ICAP model was used to analyze a randomly selected sample. The distribution of its levels can be seen in the Fig. 3. It is obvious that the distribution is generally even. Unlike the IAM distribution where most of the posts and comments are classified as 1 phase, the difference between active activities and constructive activities is less than 10%. The proportion of interactive activities is lower compared to the other two categories. But its proportion is still larger than the unrepresentative IAM categories (See Fig. 2).

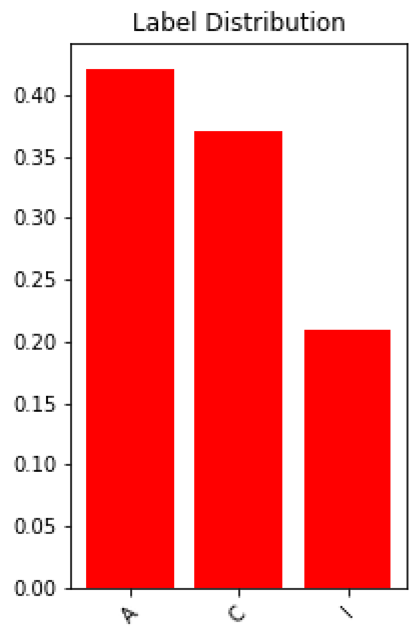

Figure 3. Distribution of ICAP Model Levels

Selection of model

The interactive-constructive-active-passive (ICAP) model and interaction analysis model (IAM) are two models used in the interaction analysis MOOC discussion forum (Tawfik et al., 2017; Wang et al., 2015). IAM was proposed to compare the nature and level of interaction in different posts or comments (Tawfik et al., 2017), however, the distribution of IAM levels for the current study is very skewed, which indicated the low differentiation of this model. On the other hand, the ICAP model demonstrated a generally even distribution. It also qualified for further analysis in this study, such as auto-classification interaction analysis and Structural Equation Model (SEM). Therefore, the ICAP was proposed as a valid substitute for IAM in the further analysis of this dissertation.

Automatic classification

The automatic classification method was used to generalize the content analysis results to all the posts and comments. The pre-labelled data obtained from 3.4.2 was randomly split into 5 datasets to perform a 5-fold cross validation: each of the 5 times, one of the datasets will be used as testing data and the other will be considered training data. Support Vector Machine (SVM) and random forest classifiers could have a precision as high as 80% when categorizing forum interaction (Pillutla, 2017). The deep learning classification methods such as artificial neural network(ANN) and long short term memory neural network (LSTM) also perform very well in the text classification tasks (Hmedna, El Mezouary, Baz & Mammass, 2017; Wei, Lin, Yang & Yu, 2017). Therefore, the SVM, random forest, artificial neural network (ANN) and long short term memory neural network (LSTM) will also be used to fit models that can classify the ACI phases in the current study.

Each model will then be applied to the testing data. For each post or comment in the testing data, the predicted ACI levels determined by the model and the pre-labelled levels analyzed by the researcher will be compared to test the precision of the model. The precision shown will demonstrate the model's validity. The model with the highest precision will be used to classify other forum data that have not yet been labeled by hand. With the help of this model, the researcher will be able to obtain reasonably precise data regarding interaction depth without handling a massive number of unstructured discussion forum threads.

Model building

Research question 1

This study investigates the factors that contribute to high-quality interaction at the individual level. The background data collected from the pre-survey focus on the relatively long-term, intrinsic traits of the learners, including each learner's gender, age, country, city, level of degree, intention to finish/earn certificate, and time to dropout, among other factors. This study centered on ordinal background features, including highest degree earned, employment status, current student status, and English-language proficiency.

The social network position data center on the learners' positions in the temporary MOOC social network, which will be measured by degree centrality, closeness centrality, and betweenness centrality. Degree centrality refers to the number of edges a node has in a network, closeness centrality is the distance from an individual node in the network to all the other nodes, and betweenness centrality is the number of shortest paths between any two nodes that pass a given node (Freeman, 1978; Takaffoli & Zaïane, 2012; Wasserman & Faust, 1994). The pre-processed forum interaction data will be analyzed through the networkX package to obtain the aforementioned metrics. After identifying the traits contributes to the length, sentiment, and depth of thread interactions, the researcher will focus on the specific interaction patterns of the top and bottom 20% of learners.

The interaction will be evaluated according to its length, sentiment, and depth. The length will be measured according to the number of words used in the interaction; the sentiment will be categorized as positive, neutral, or negative based on sentiment analysis (Balaji, Govindasamy, & Akila, 2016); and the depth will be measured using the ICAP model as is demonstrated in 3.4.2 and 3.4.3. A structural equation function will be used to investigate the extent to which each of the factors in this model influence interaction (Fig. 4). Using the parameters of the structural equation function, the contributions of the various factors will be compared.

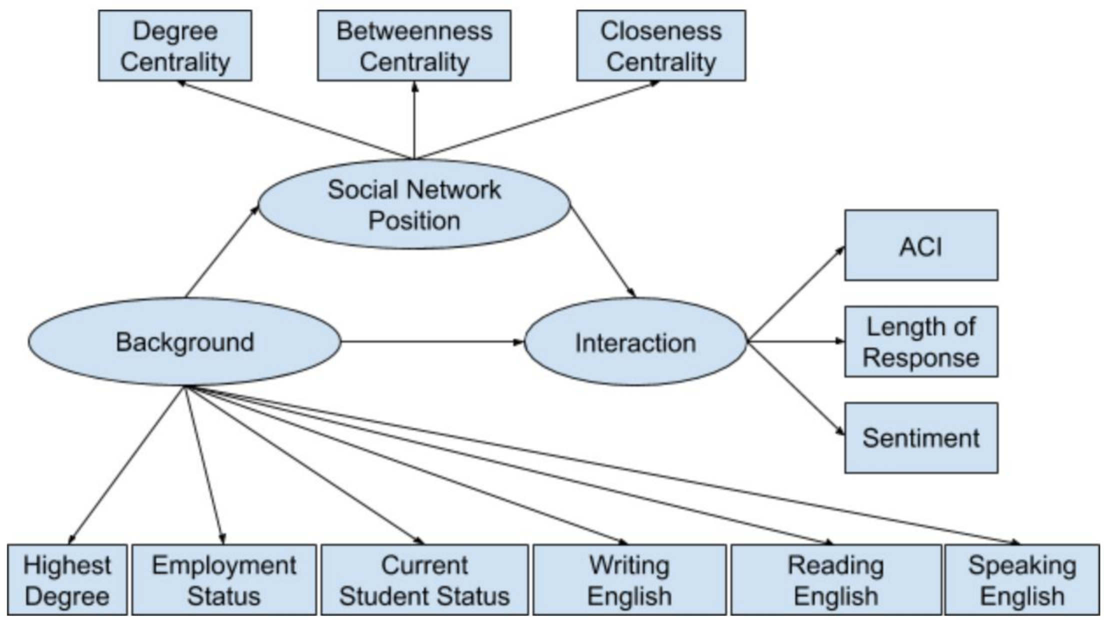

Figure 4. Theoretical model of contributions to interaction quality

Research question 2

The second research question focuses on the level of diversity between the interacting learners in each thread. The diversity of thread level interactions will be analyzed by taking the standard deviation of each trait of the learners (Formula 1) in one thread, where xi represents the trait of each learner in one thread, the x represents the average trait of all the learner in one thread, and the N represents the number of learners in each thread. The diversity in each thread will be used in the model shown in Fig. 4. Using the parameters of the structural equation function, the contribution of diversity in various factors will be compared. After identifying the traits whose diversity contributes to the length, sentiment, and depth of thread interactions, the researcher will focus on the specific interaction patterns of the top and bottom 20% of threads.

$$s = \sqrt{\frac{\sum_{i=1}^{N} (x_i - \bar{x})^2}{N - 1}}, \tag{1}$$

Chapter 4

RESULTS

Data Preparation

Background of CIC MOOC learners

A survey about learners' demographic information was given to the learners before they started the CIC MOOC. Collected demographic information included each learner's self-disclosed gender, year of birth, country of birth, current country of residence, race, level of education, current student status, level of current program, subject area(s) of degree(s), employment status, industry of employment, English-language proficiency, other languages spoken, and state of residence (United States).

The majority of the CIC learners are female (Fig. 5). The self-reported gender of 3710 learners is female, 1746 is male, and 7 is other. The number of female learners is more than double the number of male learners. The self-disclosed ages of learners range from 10 to 82. The average age is 45.4.

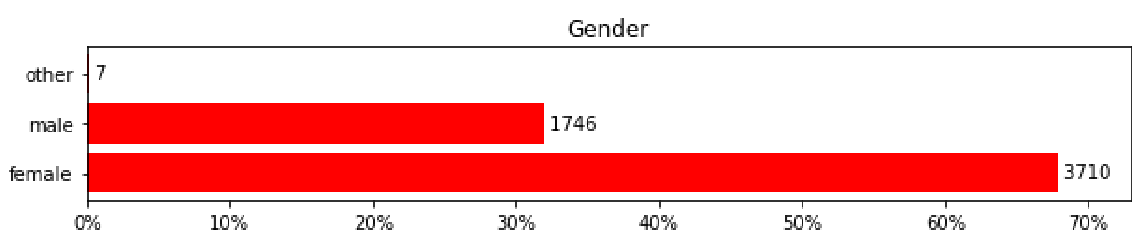

Figure 5. Distribution of gender.

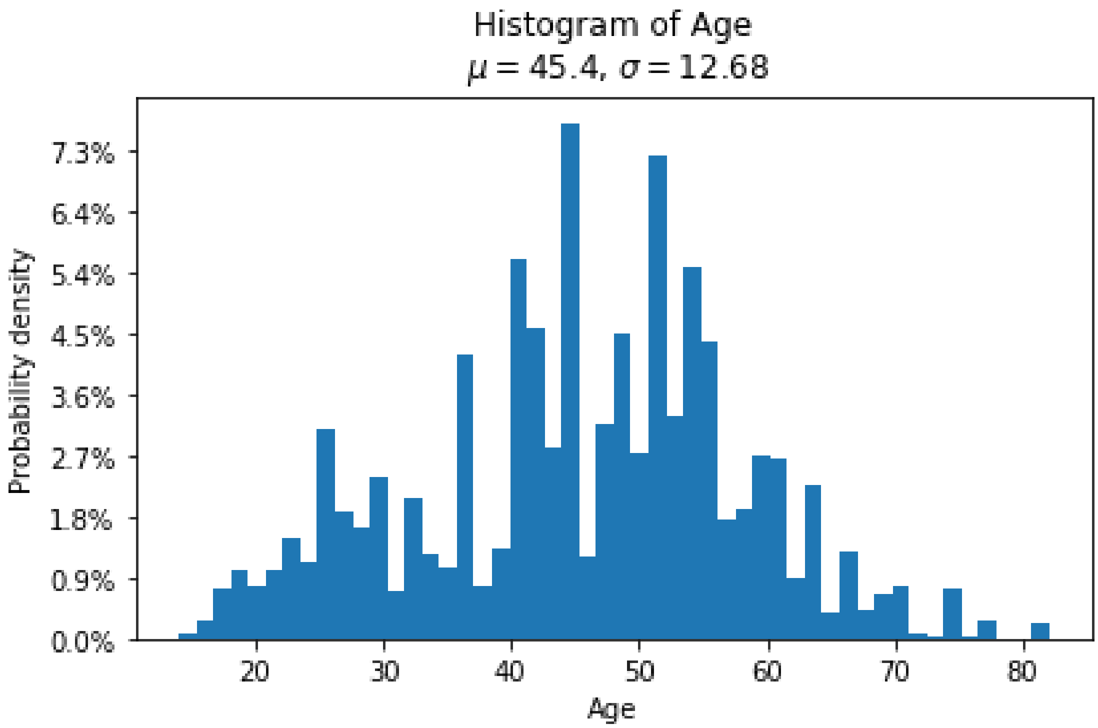

Figure 6. Distribution of age.

This study centered on ordinal background features, including highest degree earned, employment status, current student status, and English-language proficiency. Most CIC learners have a master's degree (2142 out of 5510), followed by learners who have the bachelor's degree (1646) (Fig. 7). There are 2243 learners employed full-time (35 or more hours per week), which is much larger than all other categories (Fig. 8).

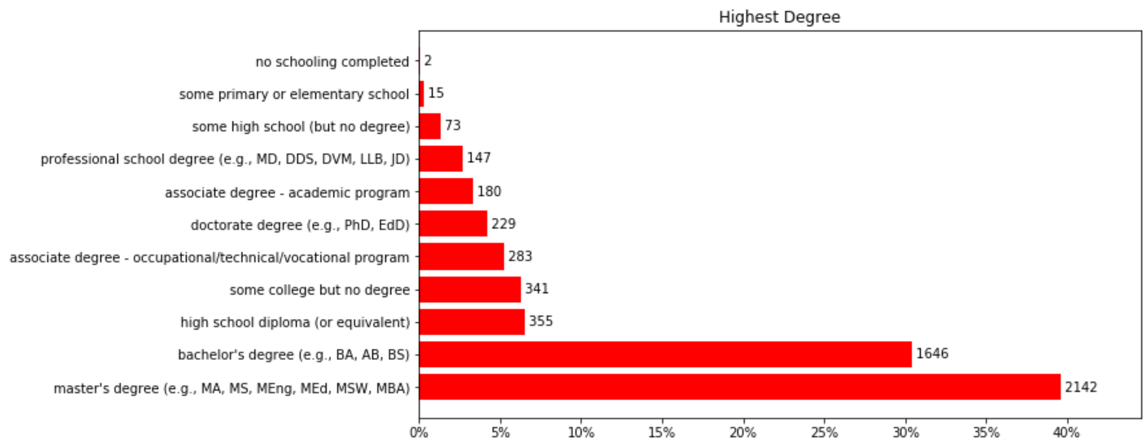

Figure 7. Distribution of highest degrees earned.

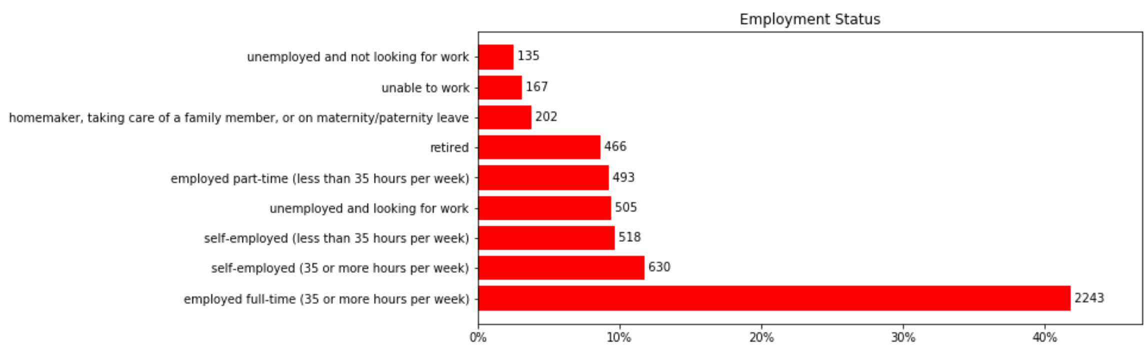

Figure 8. Distribution of employment status.

Most learners are not currently students (4479), followed by 509 full-time students and 439 part-time students (Fig. 9). The majority of learners are native speakers or proficient in writing, reading and speaking English; there are 2999, 3159, 2962 native speakers or equivalent in writing, reading and speaking English respectively (Fig. 10).

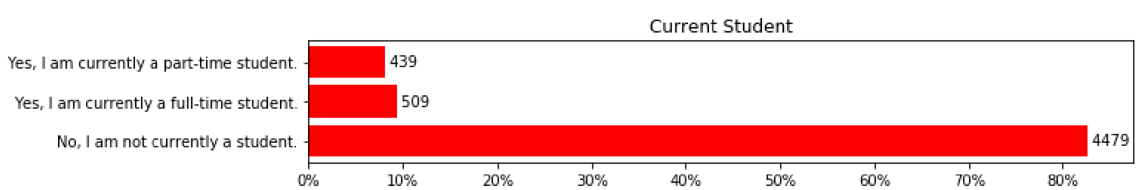

Figure 9. Distribution of current student status.

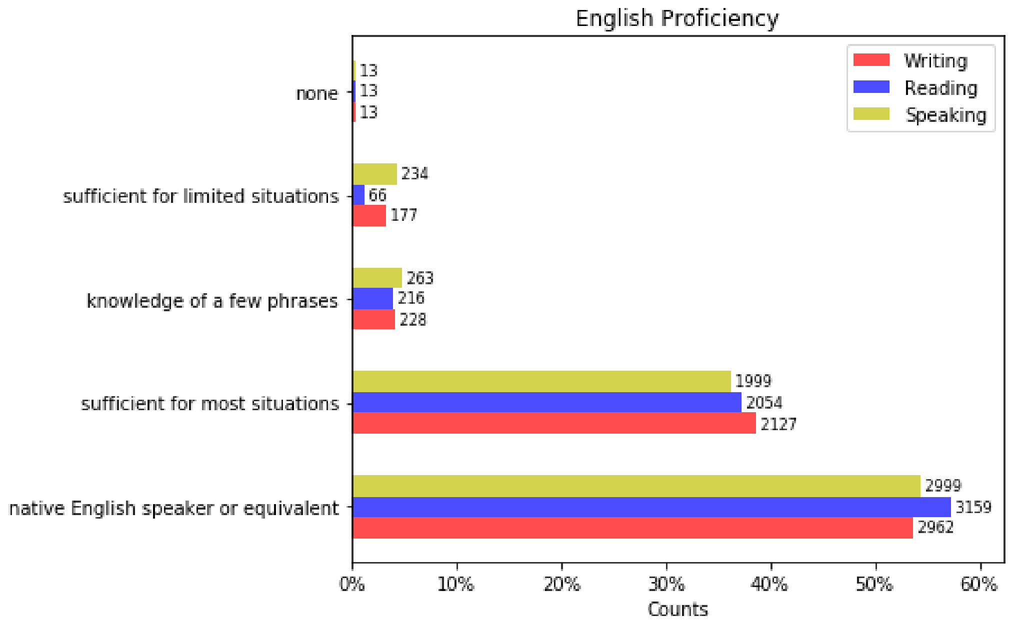

Figure 10. Distribution of English-language proficiency.

In order to balance the skewness of the background indicators, several less representative categories of highest degree, employment status, and English proficiency were combined (Table 4). The current student status only has 3 categories, so it is impossible to combine the categories.

Table 4. The levels and assigned scores for background indicators.

Indicators	**Levels**	**Scores**
Highest Degree	"some high school (but no degree)" "high school diploma (or equivalent)" "some college but no degree" "associate degree - occupational/technical/vocational program" "associate degree - academic program"	1
	"bachelor's degree (e.g., BA, AB, BS)",	2

	"master's degree (e.g., MA, MS, MEng, MEd, MSW, MBA)"	3
	"doctorate degree (e.g., PhD, EdD)" "professional school degree (e.g., MD, DDS, DVM, LLB, JD)"	4
Employment Status	"unable to work" "retired" "unemployed and not looking for work" "unemployed and looking for work"	1
	"self-employed (less than 35 hours per week)" "employed part-time (less than 35 hours per week)"	2
	"self-employed (35 or more hours per week)" "employed full-time (35 or more hours per week)"	3
Current Student	"No, I am not currently a student."	1
	"Yes, I am currently a part-time student."	2
	"Yes, I am currently a fulltime student.	3
English Proficiency	"None" "knowledge of a few phrases" "sufficient for limited situations"	1
	"sufficient for most situations"	2
	"native English speaker or equivalent"	3

Distributions of some background indicators are consistent with prior research studies on MOOCs. Most MOOC learners have a bachelor or master degree (Gillani & Eynon, 2014, Neuböck, Kopp, & Ebner, 2015), are employed full-time (Swinnerton, Morris, Hotchkiss, & Pickering, 2017). The majority of MOOC learners are also mostly reported to be native speakers (Oakley, Poole, & Nestor, 2016). Unlike other MOOCs where learners tend to report ages ranging from 20 to 34 years old (Breslow et al., 2013; Gillani & Eynon, 2014; Neuböck, Kopp, & Ebner, 2015; Palin, 2014; Perna et al., 2014), learners in the CIC MOOC have an average age of 45.4. Thus, in most aspects the demographic of the CIC MOOC participants matches the demographics of MOOCs at large.

Social network analysis

A social network analysis was conducted to evaluate social network position in the CIC MOOC discussion forum. The analysis was conducted with the assistance of a widely used social network analysis Python package, NetworkX. Because Coursera has structured discussion forums, we used the reply structure to form the social network for the selected forums. However, the post_id in the dataset was incomplete, as the dataset does not include the post_id of each comment. In other words, it was impossible to build a network presenting the links between comments and posts. I accordingly built a fully connected social network within each thread. A directed link was created from the last commenter to each of the earlier posters within same thread.

For instance, no post id was recorded in thread 48 (table 5.a). It is impossible to know whether Karl only replied to Zachary's post in this thread, or whether Karl and Zachary both replied to Darlene' post. Therefore, this study built a fully connected social network within each thread. Directed links were created from the last poster to each of the earlier posters within same thread. In such a case, the network built according to this thread had 3 links: the link from Zachary to Darlene, from Karl to Darlene, and from Karl to Zachary (table 5.b).

Table 5. Social network construction.
a. The structure of CIC MOOC dataset.

Thread ID	**Post ID**	**Local Time**	**Pseudonym**
48	NaN	2013-09-01 04:33:29	Darlene
48	NaN	2013-09-01 10:35:49	Zachary
48	NaN	2013-09-02 16:05:04	Karl

b. The network built based on the structure of CIC MOOC dataset.

Thread ID	**Source**	**Target**
48	Zachary	Darlene
48	Karl	Darlene
48	Karl	Zachary

Threads featuring only one learner who never received a reply were removed from further analysis. After removing these learners, 730 users remained. After building the social network, I calculated the centrality degree, betweenness degree, and closeness degree for each of the learners in the selected forums. The distribution of degree centrality, betweenness, and closeness shown in Fig. 11, 12 and 13 indicates that the CIC MOOC social network is a sparse network that follows a long tail distribution. Most learners did not connect to very many of their peers, and only a few learners had very high centrality.

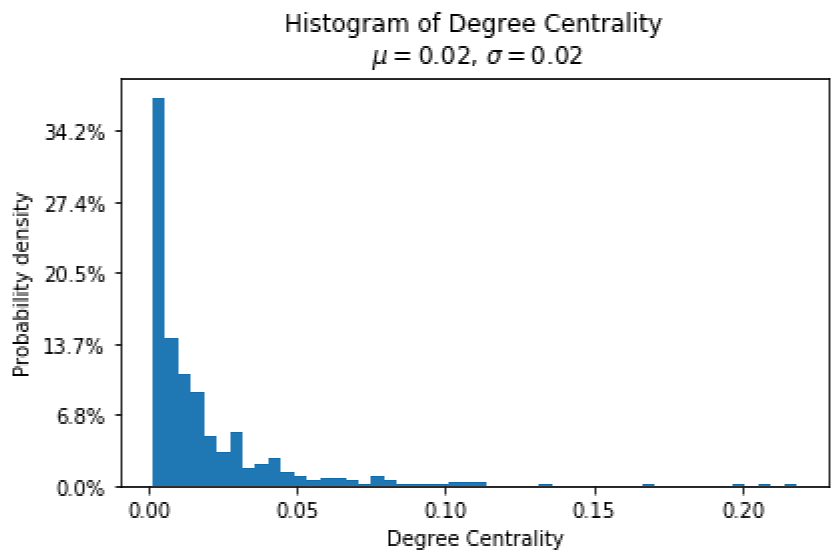

Figure 11. Distribution of degree centrality.

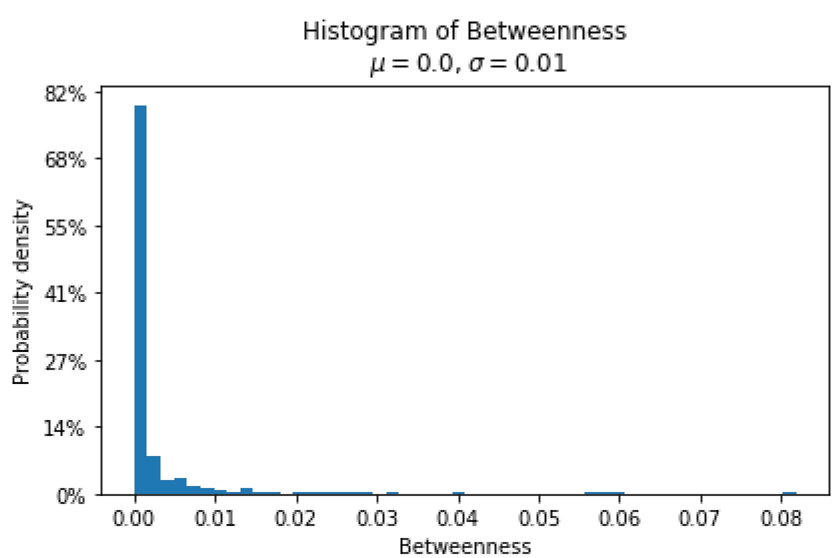

Figure 12. Distribution of betweenness centrality.

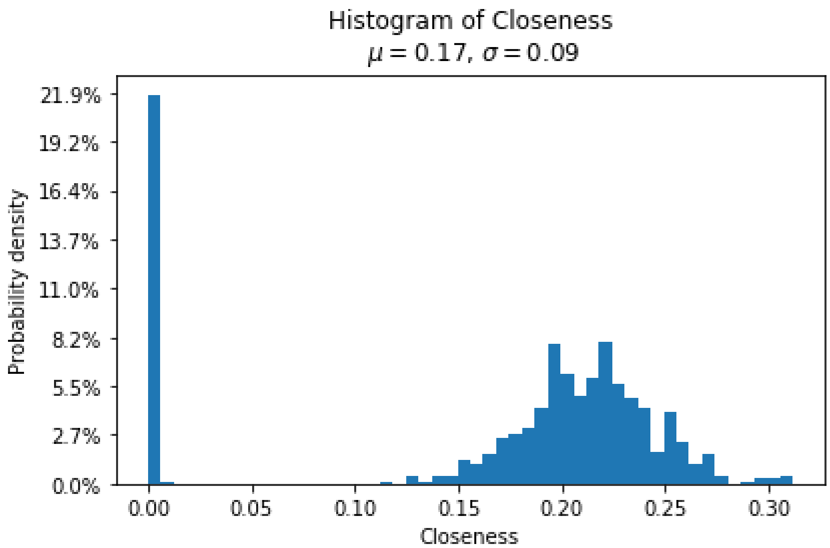

Figure 13. Distribution of closeness centrality.

The CIC MOOC learner's interaction

Length of interaction

One of the quantitative features of MOOC discussion forum interaction is the length of posts and comments. Length was evaluated by the number of English words in each post or comment. Numbers were not counted as words. The length distribution can be seen in Fig. 14. The number of English words in a post range from 1 to 974. The average number of English words in a post or comment is 65.61. The post or comment length for each learner was standardized for further analysis.

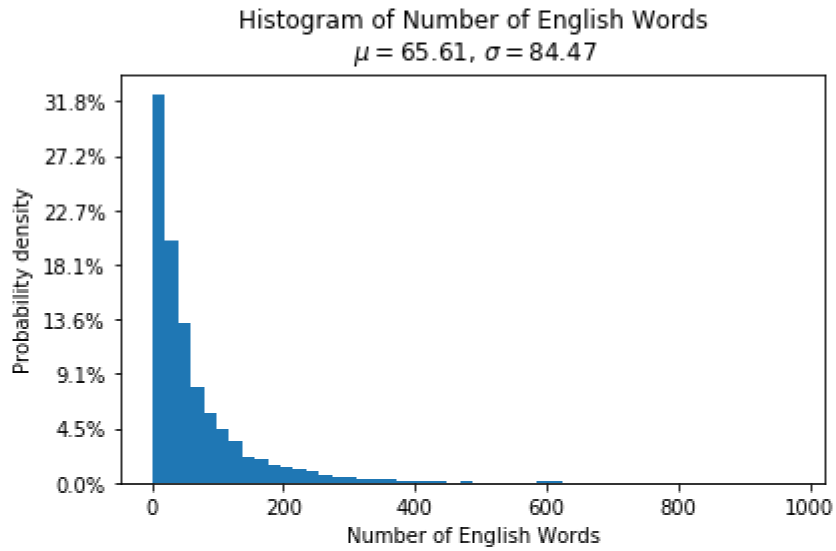

Figure 14. Distribution of post or comment length.

Sentiment analysis

The sentiment of each post or comment was evaluated via sentiment analysis. The well-developed Python library *TextBlob* was used to conduct the sentiment analysis. The performance of TextBlob has been validated with the twitter dataset. It is able to well identify negative events discussed in tweets, and the sentiment polarity of the tweet text alone is consistent with the emoticons in the same tweet (Wang, Yuan, & Luo, 2015). This library has a lexicon with commonly used English words and their sentiment polarity. The sentiment polarity of a sentence is calculated by averaging the polarity of each word with a non-zero polarity. Table 6 shows 2 examples of the calculating process. Table shows 7 examples from negative to positive sentiment polarity. Figure 14 shows that the average sentiment on the MOOC is neutral to positive. The sentiment polarity ranges from -0.83 to 1. The average sentiment polarity in a post or comment is 0.25.

Table 6. Sentiment polarity of sentences by TextBlob library.

Place Table Here

Picture	is	so	smal	:(									Total
0	0	0	0	-0.75									-0.75
I	know	I	am	a	little	late	Can	I	still	join	your	group	
0	0	0	0	0	-0.188	-0.3	0	0	0	0	0	0	-0.244

Table 7. Examples of Sentiment Analysis.

Post or Comment	**Sentiment**
Picture is so smal :(	-0.750000
I'm sorry as I have no answer for you, but cou...	-0.625000
If your center is self would some people perce...	-0.382857
I know I am a little late. Can I still join y...	-0.243750
I vote for the second one, the one with straig...	0.100000
I love Edison and Simone Weil's quotations !	0.625000
this is a very beautiful and creative work Ami...	0.812500

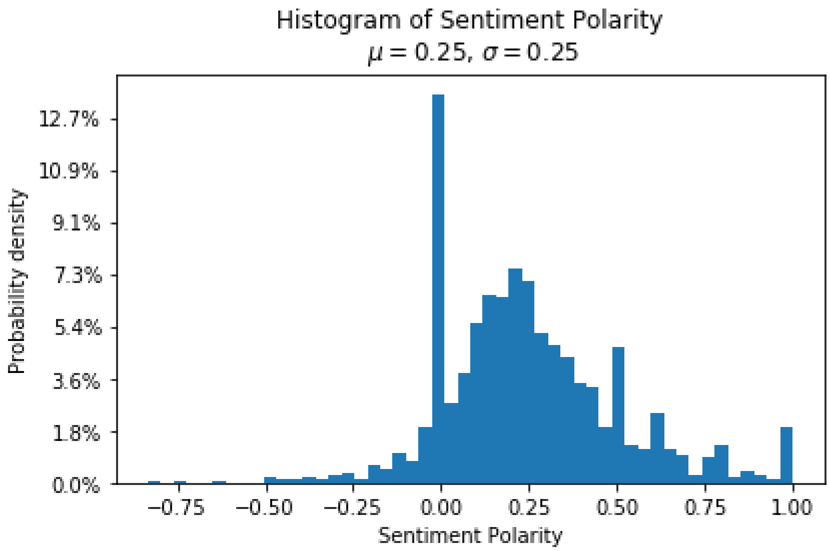

Figure 15. Distribution of sentiment polarity.

Interactive-Constructive-Active-Passive (ICAP) model

According to the coding scheme in Table 3 of Chapter 3, two raters rated 100 posts and comments randomly selected from the discussion forum. After several rounds of discussion, the interrater reliability reached the agreement level of 0.855 (Cohen's kappa), which is considered to be an indicator of perfect agreement (Landis & Koch, 1977). This study took a random sample of posts and comments from the discussion forum to ensure the representativeness of the sample. Such data sampling method inevitably led to the breakdown of threads and the obscuring of the discussion context. In order to maintain the consistency and validity of this framework, the content analysis was strictly based on the evidence observed in the posts and comments with no unwarranted inference or assumption.

One rater then analyzed another randomly selected sample of 1000 posts and comments using the ICAP model. The distribution of this sample can be seen in Fig. 3 in Chapter 3. It is clear from looking at this figure that the distribution is generally even. The difference between active activities and constructive activities is less than 10%. The proportion of interactive activities is lower than the proportions of the two other categories.

Automatic classification with deep learning methods

The top 20 words used most frequently by CIC learners are 'idea,' 'project,' 'like,' 'thank,' 'people,' 'also,' 'hi,' 'help,' 'well,' 'start,' 'need,' 'course,' 'write,' 'creative,' 'learn,' 'http,' 'love,' 'thread,' 'really,' and 'much'. The words found at least ten times each in the discussion forum were used as predictors to estimate the interaction phase in each post or comment. The remaining words numbered 2,127 (22% of the terms), which constructed 86.5% of the vocabulary used in the discussion forum (Fig. 16).

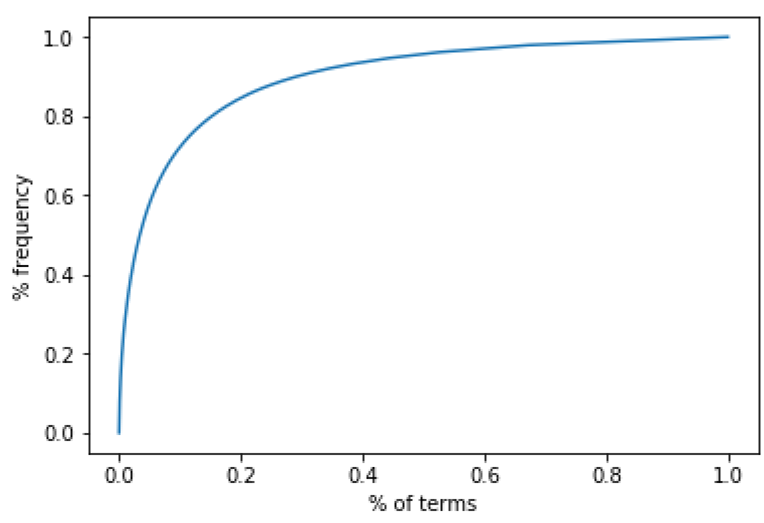

Figure 16. Relationship between term proportion and term frequency.

A series of machine learning classifiers were used to predict the ICAP levels of the unlabeled posts and comments. The classifiers are algorithms that are used to predict the categories of data points according to a pre-labelled dataset. The classifiers tested in this study were support vector machine (SVM), random forest (RF), artificial neural network (ANN), and long-short-term-memory neural network (LSTM). They are widely used in text classification tasks (Hmedna, El Mezouary, Baz & Mammass, 2017; Pillutla, 2017; Wei, Lin, Yang & Yu, 2017). The SVM fits a separating hyperplane to classify high dimensional data into different categories. The random forest classifier assembles multiple tree-based structures to achieve the same goal. ANN and LSTM are algorithms that mimic biological neural networks, which assemble multiple algorithms as neurons in a multi-layer framework. Descriptions of the actual processes of these classifiers are outside of the scope of this paper.

A 5-fold cross validation was applied to all the models mentioned above. The pre-labelled dataset was separated into 5 equal subsets; each one was used as testing set while the other 4 were used as training sets. The classifier learned the relationship between each training set and its categories, then used the rules it learned to fit the category of testing set. The accuracy rate is the rate of correctly predicted posts over all the posts. The parameters of each classifier were tuned to achieve the classifier's best performance. The accuracy rate of each model is shown in Table 8.

From Table 8, we can see that the best classifier is LSTM. The accuracy rate of this classifier is 79.3%. To evaluate the eligibility of the classifier to rate the rest of the posts and comments, the interrater reliability between the human rater and the machine learning classifier was calculated via Cohen's kappa. Cohen's kappa is used in both machine learning algorithms evaluation (Ben-David, 2008) and inter-rater reliability of human raters (Landis & Koch, 1977). The Cohen's kappa between the human rater and the classifier is 0.68, which indicates substantive agreement (Landis & Koch, 1977). Therefore, the LSTM classifier was selected to rate the interaction level of the uncategorized posts or comments.

Table 8. Performance of Different Classifiers.

Classifier	**Parameters**	**Accuracy**	**IRR**
SVM (rbf)	C:1.0, gamma:'scale'	0.675	0.440
SVM (linear)	C=1.0	0.545	0.273
RF	'n_estimators': 400, 'min_samples_split': 10, 'min_samples_leaf': 4, 'max_features': 'auto', 'max_depth': 70, 'bootstrap': True	0.670	0.468
ANN	Number of layers: 3 Number of neurons: 128	0.675	0.439
LSTM	Number of Bi_LSTM Layers: 2 Number of Bi_LSTM Neurons: 64 Number of Fully Connected layer: 2 Number of Fully Connected Neurons: 256	0.793	0.676

The performance of the LSTM classifier is shown in Fig. 17. It captures the semantic features of 87.5% active activities, 82.1% interactive activities, and 76.0% constructive activities. In the randomly selected 200 posts and comments, the classifier incorrectly categorized 7 active activities into constructive, and 3 into interactive. It also failed to capture the features of 14 constructive posts or comments, by categorizing 6 as active and 8 as interactive. There were 10 interactive posts and comments categorized incorrectly, 6 were categorized as constructive and 4 were categorized as active.

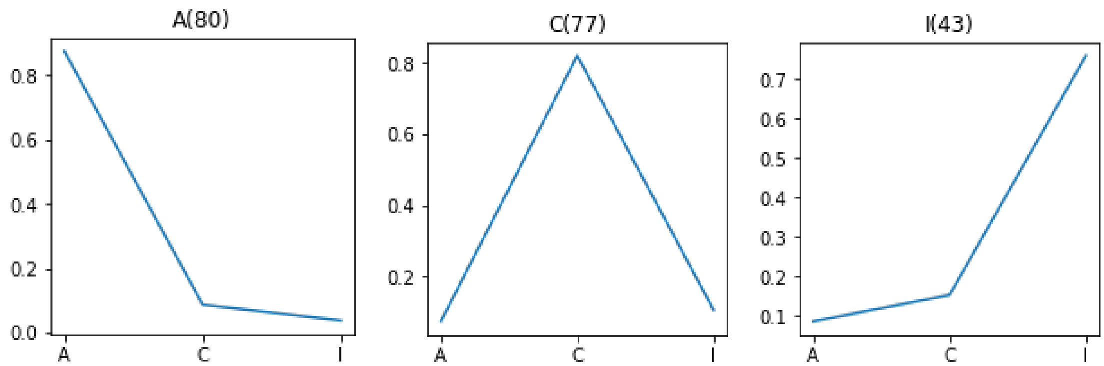

Figure 17. Performance of the LSTM classifier at each interaction level.

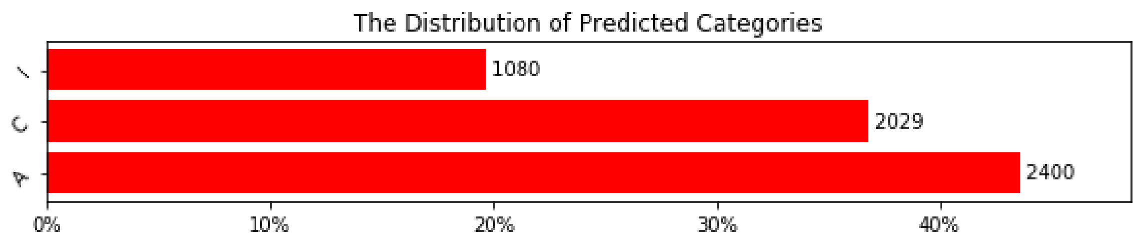

Figure 18. Distribution of ACI categories.

Some examples of the LSTM model can be seen in table 9 and these demonstrate the performance of LSTM on the test set. It shows the ACI categories of the posts or comments as predicted by the classifier and as evaluated by a human rater. The distribution of the categories of all the posts and comments is shown in Fig. 18.

Table 9. Examples of LSTM Classifier.

Post or Comment	**Predicted Category**	**Actual Category**
Thank you, Roberta. You asked a very good question. We should definitely collaborate on this. Thanks!Julia	A	A
Here's the lost link:https://class.coursera.org/cic-001/wiki/view?page=peer_practice	A	A
For those familiar with http://www.safaribooksonline.com/ and https://github.com/, I see my project as a kind of combination of the two ideas - maybe it should be called KnitHub :)Safari has several differenet levels of subscription and gives access to thousands of technical books. You can access books that are currently being written - rough cuts - and are able to add comments to them. You can read books on their special apps for tablets, phones and laptops.Github is a repository and source control system, where you can store code and keep a history of changes to it. Also you can fork code to create different branches and versions.	A	C
Thank you Jollean,I have never experimented with stones, but what a great idea!! My biggest challenge will be how to drill holes and to attach them to the main base. . Thank you!!Tiffany	A	I

Thank you!I might be turning the "old" blog into something else, and work on a new one...still thinking about it, but I would like to write about expat life, and how to overcome some cultural problems of communication when you don't live in your Country.	C	C
Hello,After sitting down and doing a couple painting set ups one with water color and a second with acrylics I decided to go with colored pencils. I attempted, failed and tried again. This would be the first time in along time that I had attempted and failed, but looked at in in a different light that it was okay that my first two didn't work, that it was okay to try something else. It has been a long time since I painted and it is not something that I can just pick up a brush and do. I am attaching what I have done so far.	C	C
thanks for your kind words Victoria. i am sure you will be able to achieve your goal soon. lets begin the journey :) :)	C	A
A misunderstanding for sure. I understood your structure to expect the incumbent to struggle with that set of seemingly contradictory competencies, which may not be the case if one were to match the profile for this job with that of the incumbent. It's common practice for management to use profiling for this purpose so I'm not sure what it is that you're on about. The link is	C	I

to share information pertaining to this. Don't bother replying and delete what you want.		
You're very lucky that creativity comes so easily for you, Patricia; I have to work very hard at it myself. However, I do find the same thing to interfere with my creativity that you do: too many errands, chores, and phone calls delegated down to me on my own time. Also, an excessively negative home or work environment totally interferes with creative thought for me.	I	I
Elin,Your title pulled me into this stream. I love your idea. I believe my students would love to read this. It would make a great book. I would love to see the juxtaposition of your entry written before you have done it and then the reality of having done it: your thoughts on the first kiss, your fantasy about the first kiss, and then your actual first kiss.I think you have a brilliant idea. Make the time for it.Diane	I	I
Hi, Im Heather and I was wondering if anyone had heard of earthships or biotecture. The premise is to use whatever items we have around to create sustainable living that is adapatable to the particular climate we are in. There are several ideas like glass bottle walls and rocket stoves. One project idea could be to see if there are easy sustainable ideas that may help local homeless encampments. Or maybe just a campaign to spread awareness of	I	C

the possibility of living in a more eco friendly way that s easy with some small inventions. Feedback would be great and any other project ideas relating to steering humanity to a more sustainable future I would love to get in on.		
guys are doing a project or not??? should we try something together??	I	A

Research Question 1. The Relationship Among Individual Background, social network position and Interaction

Relationship for all the learners

The first research question of interest is the relationship among background, social network position, and interaction. There were 730 individual learners who posted or commented in the selected forums. A structural equation model (SEM) was used to investigate the relationship among individual background, social network position, and interaction. To interpret the results, this study follows the cut-off of prior research (Comrey & Lee, 1992; Tabachnick & Fidell, 2007) and addresses the standardized loadings that are below 0.32 as very weak, above 0.32 as weak, above 0.45 as fair, above 0.55 as good, above 0.63 as strong, and above 0.70 as very strong. The SEM model is fitted based on correlation matrix, and this set of cutoffs can be used to interpret the correlation coefficient (Comrey & Lee, 1992). Therefore, these cutoffs are used for a clear interpretation. Meanwhile, it worth noticing that the loadings coefficients are still the most precise indicators for the relationships of interest.

At the individual level, the relationship among individual background, individual social network position, and individual interaction level is shown in Fig. 19. An individual learner who has a higher degree (highest degree), longer working hours (employment status), longer current formal learning hours (current student status), and better English-language proficiency (writing/reading/speaking English) is considered to have a strong academic and vocational background. Meanwhile, an individual learner who is connected to more learners (degree centrality), engaged in more shorter paths in the social network (betweenness degree), and/or is close to all other nodes in the network (closeness) is considered to have high social network position. This model captures whether an individual learner with a stronger academic and vocational background and/or higher social network position is more likely to provide a post or comment that is longer (length of response), more positive (sentiment), and engaged with higher cognitive processes in the interaction (active/constructive/interactive levels).

The three latent variables of interest and their indicator variables are presented in Fig. 19. Background is very strongly connected to English-language writing proficiency, reading proficiency, and speaking proficiency (0.98, 0.95, 0.95). It is very weakly connected to highest degree and employment status (0.21, 0.23) and is not at all connected to current student status (0.05, $p = 0.073$). As Fig. 9 indicates, the distribution of current student status is very skewed. Most learners are not current students, which could make this indicator variable less informative in the model.

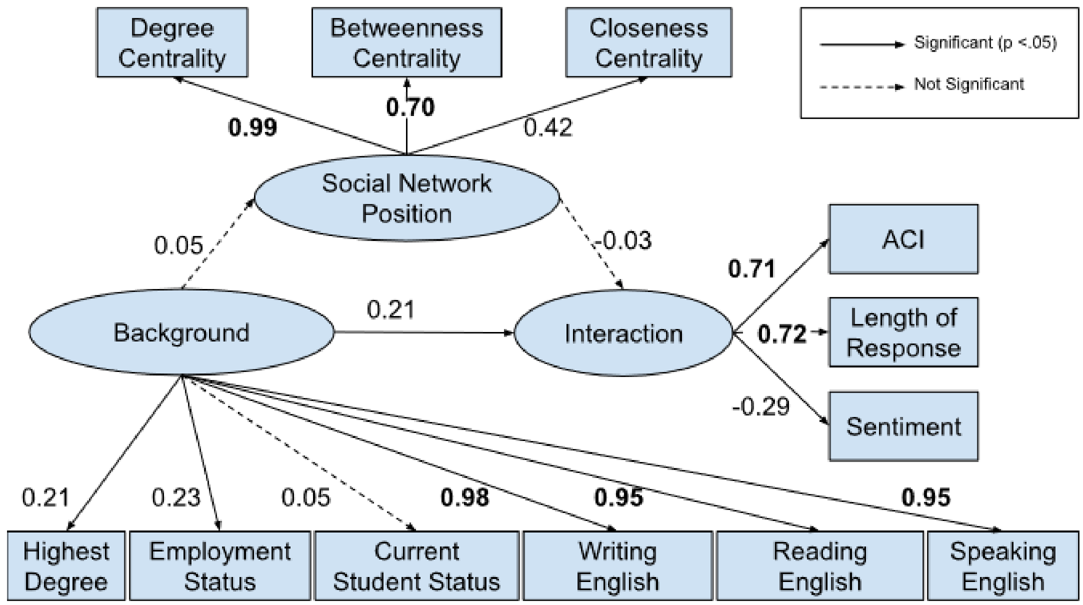

Figure 19. Relationship among individual background, social network position, and interaction for all 730 learners.

Social network position is very strongly connected to degree centrality and betweenness centrality and moderately connected to the closeness centrality (0.99, 0.70, 0.42). Interaction is very strongly connected to the Active-Constructive-Interactive level and length of response (0.71, 0.72). Unlike the Active-Constructive-Interactive level and length of response, sentiment polarity is negatively and very weakly related to interaction (-0.29).

The SEM model indicates that there is no connection between background and social centrality (0.05, p = 0.099) and no connection between social network position and interaction for MOOC learners (-0.03, p = 0.613). A very weak connection is found between background and interaction (0.21), which indicates that an increase in each indicator variable associated with background is very weakly related to the increase in ACI level and length of response and to the decrease of sentiment polarity.

Background cannot predict social network position, and social network position cannot predict interaction. It indicated that whether a learner has a better academic and vocational background does not predict the number of connections the learner makes in the discussion forum. Similarly, a learner who makes more connections within the social network does not necessarily have longer and higher-level interactions.

Relationship for the top 20% learners with highest ACI score

This study also aimed to determine the characteristics of learners who generally engaged in higher-level interactions (constructive and interactive) and those who generally engaged in lower-level interactions (active). Therefore, the upper group should contain the learners/threads that are mostly constructive or interactive, which is equivalent to an average ACI score equal or larger than 2.0. The top 20% (150) learners all have average ACI scores higher than 2 (Fig. 20), which indicates that they consistently created constructive and interactive posts or comments. Similarly, average ACI score for bottom users/threads should be closed to 1. Therefore, the bottom 20% (150) learners all have average ACI scores smaller than 1.35 (Fig. 20). Therefore, the top and bottom 20% learners in regard to ACI scores were analyzed independently as focus groups.

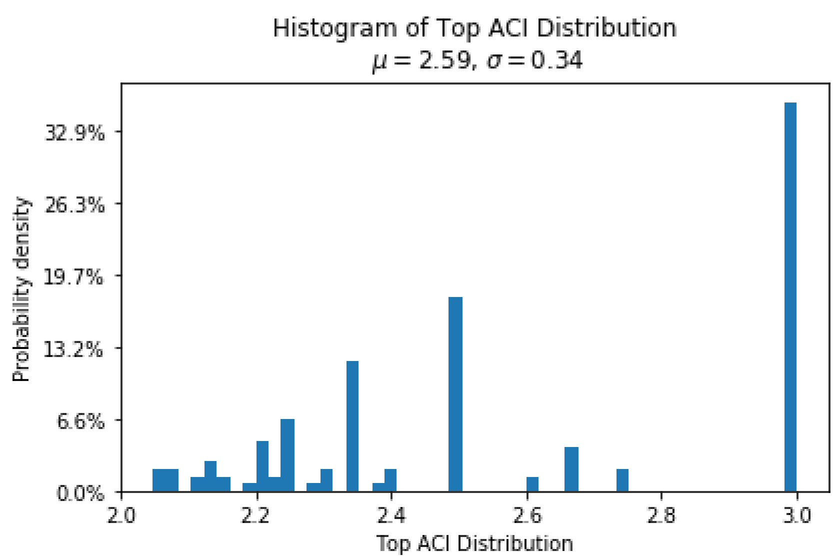

Figure 20. Distribution of learners with top 20% ACI scores (n=150).

Fig. 21 shows the relationship among background, social network position, and interaction for the top 20% of learners with the highest ACI scores. Compared to the general model that considers all the students, Fig. 21 indicates multiple changes for the top 20% of learners. For the indicator variables, the current student status starts to contribute to the background and has a negative and good connection to the background (-0.58). Meanwhile, the length of response and sentiment polarity are no longer related to the interaction for the top 20% of students (-0.11, 0.02). The connections between the other indicators and their latent variables remain the same level as all the learners.

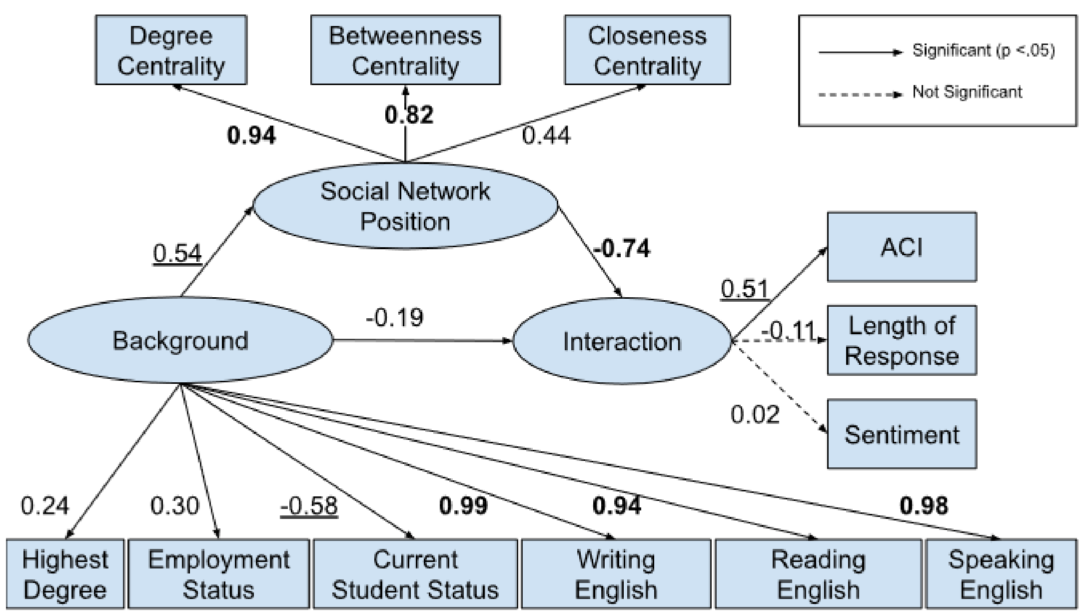

Figure 21. Relationship among individual background, social network position, and interaction for learners with top 20% ACI scores (n=150).

For the latent variables, the background can fairly predict social network position (0.54). For the top 20% of learners, their strengthened academic and vocational background can be used to help predict whether they made more connections in the MOOC discussion forum. Background is very weakly and negatively related to interaction (-0.19), which means an increase in each indicator variable of background is very weakly related to a decrease in the ACI level.

Social network position can very strongly and negatively predict (-0.74) interaction. Among the top performers, the learners who connected and bridged less frequently tend to leave posts or comments that were more interactive. The learners who connected more tended to post or comment at a lower level. Since the average score for all the learners in this group is higher than 2 (constructive; see Fig. 20), the lower level for the top learners is the constructive level.

Relationship for the bottom 20% learners with the lowest ACI scores

The bottom 20% (150) learners all have average ACI scores lower than 1.35 (Fig. 22). The majority have scores of 1, which indicates that they consistently created active posts or comments. Fig. 23 shows the relationship among background, social network position, and interaction for the bottom 20% of learners with the lowest ACI scores. For the indicator variables, current student status still contributes to and is negatively correlated with background, but the extent to which it influences background shrinks from -0.58 to -0.10. Meanwhile, the length of response and sentiment polarity are not related to the interaction for the bottom 20% of students (0.11, 0.01). The connections between the other indicators and their latent variables remain the same level as all the learners.

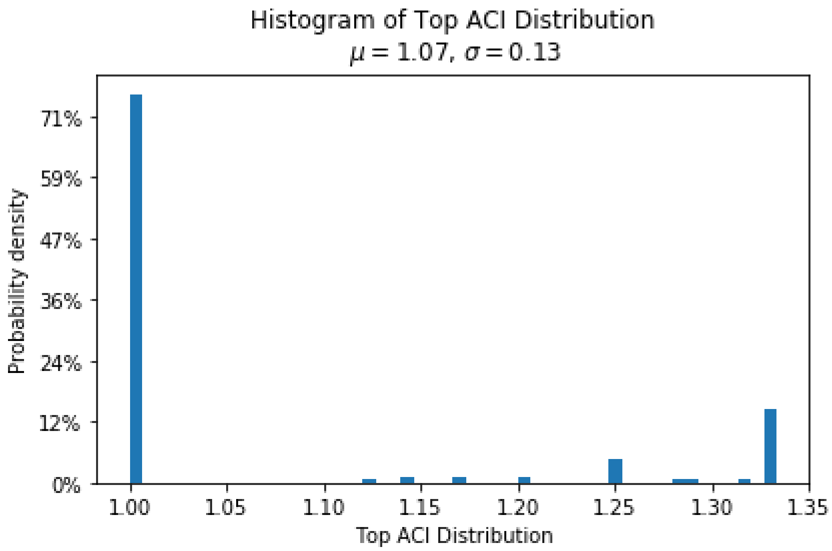

Figure 22. Distribution of learners with bottom 20% ACI scores (n=150).

For the latent variables, the background is no longer able to predict social network position (-0.06) or interaction (-0.01). However, social network position can fairly and positively predict (0.49) interaction (Fig. 23). Among the bottom performers, the learners who connected and bridged more tended to leave posts or comments at a higher level. Since the average score for all the learners in this group is less than 2 (constructive; see Fig. 22), the higher level for the bottom learners is also the constructive level.

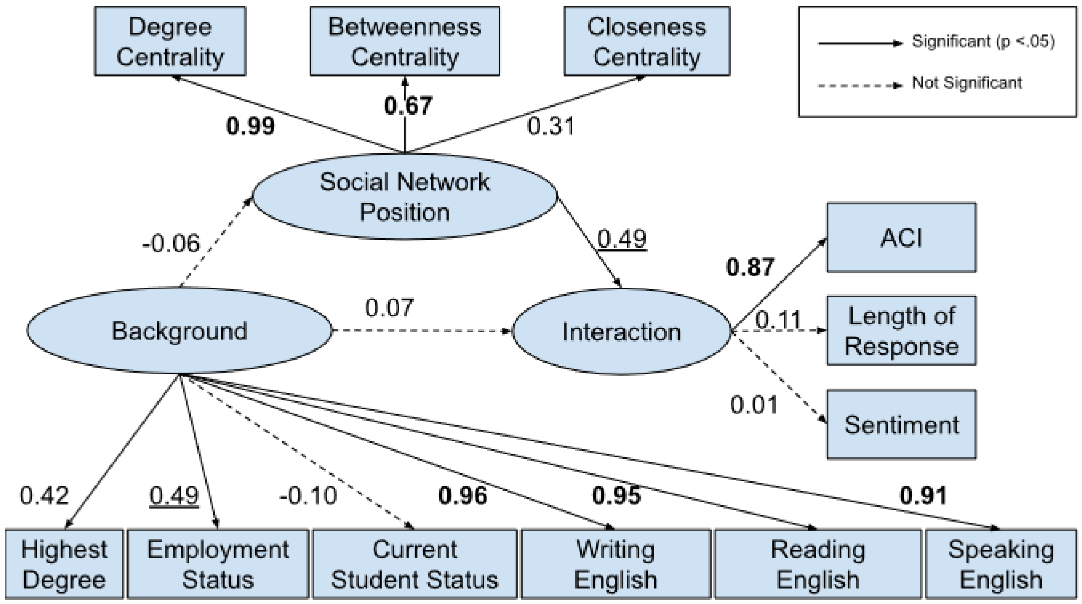

Figure 23. Relationship among individual background, social network position, and interaction for the learners with bottom 20% ACI scores (n=150).

Summary of research question 1

Different relationships among background, social network position, and interaction were identified for different groups of CIC MOOC learners. Only background can very weakly and positively predict interaction for all the learners. However, for the top 20% of students with the highest ACI levels, both background and social network position are negative predictors for interaction. Meanwhile, the background is a moderately positive predictor for social network position. Although coefficient symbols of the connection between social network position and interaction are reversed for the top and bottom 20% of learners, they all indicate that learners who made more connections in the discussion forum tended to leave constructive, rather than active or interactive, posts and comments.

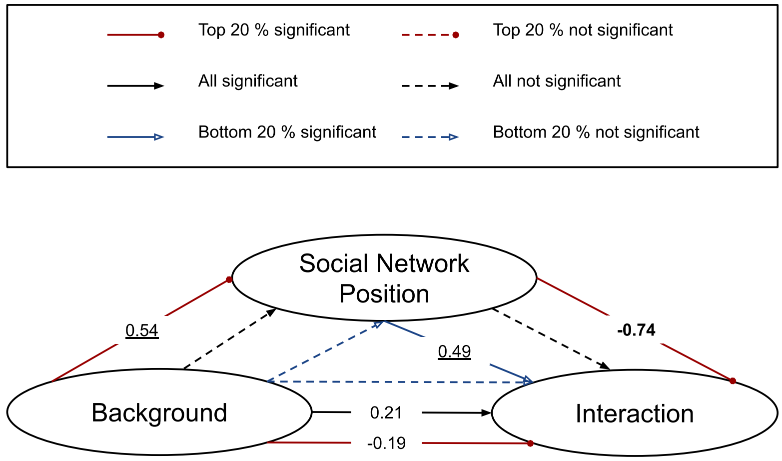

Figure 24. Relationship among individual background, social network position, and interaction.

English-language proficiency generally makes the largest and a very strong contribution to background, while degree centrality always contributes the most to social network position. The contribution of sentiment analysis is negative (-0.29) for all the users, while the ACI and length of response are positive (0.72, 0.73) for all of the users. This indicates that the longer posts or comments with a higher ACI level often expressed mildly negative sentiment.

Because this research investigated multiple indicators, two examples are used to demonstrate the practical implication of this model. One of the top 20% of students with highest average ACI is Cora (pseudonym). Cora is a female, was born in 1952. She has a professional degree (e.g., MD, DDS, DVM, LLB, JD), is not a current student and is employed part-time. She considers herself as a native speaker or equivalent for writing, reading and speaking English. Her standardized degree centrality, betweenness centrality and closeness centrality are 0.0233, 0.0004, and 0.2296 correspondingly, which is greater than 76.2%, 67.0%, and 78.5% learners. Cora's posts and comments are recorded in Table 10.

Table 10. Content, length, sentiment and level of posts and comments left by Cora.

ID	Text	Length	Sentiment	ACI
459	I agree. The Artist's Way is great. Am an artist and this is one of the books we studied.	19	0.80	A
2340	This is a great idea! There is much material on the Web for teachers to support this project. Start with small greenhouses -5-6 feet by 2 feet wide by 1 foot deep. In cold climates, these can be moved against buildings to protect produce being grown. Winters could be for herb growing as well. In Michigan, we have harvested parsley under the snow.	51	0.04	C
2443	Having served on a Board of Education, I have a different perspective. I think it will be quite difficult to make a new model that can be utilized for education, but I agree with Pauline. This could be an interesting project.First, a goal might be to enhance time and efficiency in the educational setting. Or maybe the goal could be how we get kids to become lifelong learners. WHAT should be learned, WHO/what should teach it and HOW it should be delivered would all be important components. We need to be creative! You could put this into a business model and change individual aspects which may produce different results. The focus	183	0.14	I

	on what should be learned shifts as societal needs change, but many of the basics are the same as 100 years ago. Delivery systems are different, though. What can we do with these? You'd need to also consider the attitude and educational level of teachers when making changes. It might take a while to get faculty members on board, even if they were in on the changes. This would make it difficult to implement the model, without many years of hiring right and retiring the staff. This has been my experience.			
2224	Creativity is all around us. If we look back at paths we have taken when a wall has presented itself before us, and we pushed to get to the other side, we can see examples of our own creative evolution. Probably not Steve Jobs, but actionable. It's harder to take the concepts and apply them to the idea than to think of the idea and apply the analysis, change the variables. I have found reading the discussion forums has helped formulate a tangible idea or two. Hope it helps you.	78	0.18	C

Julia (pseudonym) is one of the bottom 20% of students with lowest average ACI. Julia is a female, was born in 1951. She has a bachelor's degree (e.g., BA, AB, BS), not a current student and is employed part-time. She considers herself as a native speaker or equivalent for writing, reading and speaking. Her standardized degree centrality, betweenness centrality and closeness centrality are 0.0192, 0.0000, and 0.2119 correspondingly, which is greater than 71.4%, 0.0%, and 59.2% learners. Julia's posts and comments are recorded in Table 11.

Table 11. Content, length, sentiment and level of posts and comments left by Julia.

ID	**Text**	**Length**	**Sentiment**	**ACI**
416	Here is the best creation but I made it before I saw the video in which it was specified that we could only use paper. I did it again with torn paper and came up with a similar result but instead of 13 inches it was only 10.	19	0.80	A
416	Using torn paper and no glue!!!! TADA!!!	51	0.04	A

Cora and Julia have similar backgrounds except that Cora has a higher educational degree than Julia. This difference co-occurs with the fact that Cora has a higher average ACI level (2.0) and length of response (82.75) than Julia (ACI: 1.0; length: 35.00), which demonstrates contribution of background to the ACI level and length of response. Meanwhile, Cora has an average sentiment polarity of 0.29, and Julia has 0.48. This shows posts or comments with higher ACI level are not as positive as lower level.

Meanwhile, Cora and Julia have similar social network position, but this doesn't lead to similar interaction levels, which demonstrated the insignificant relationship between social network position and interaction. Since the model captures statistically significant features for all the observations in the dataset, the features from the 2 specific examples provided here are only for demonstration purpose. They do not imply any conclusions that go beyond the models.

Research Question 2. The Relationship Among the Thread Diversity of Background, Social Network Distance, and Interaction

The other research question of interest is whether the similarity or diversity of background and social network contribute to interaction in a group. Discussion forum threads are learner-generated groups with discussions centered on clearly identified topics. Wong, Pursel, Divinsky, and Jansen, (2015) indicated that for MOOC discussion forums: “A thread is created for initiating a new discussion. A post is a message for replying to a thread. A comment is a message used to reply to a post.”. The variation in each learner’s background and social network position in each thread is calculated as the deviation from each group. The average ACI level, length of response, and sentiment polarity of all the learners in each thread are used as the indicator variables of interaction.

Relationship for all the threads

For the all the threads, the relationship among thread diversity in background, social network position, and the thread average interaction level is shown in Fig. 25. A thread that has learners with a larger variation in highest degree, employment status, current student status, and English-language proficiency (writing/reading/speaking English) is considered to have a higher background diversity. Meanwhile, a thread that has learners with a larger variation in degree centrality, betweenness degree, and/or closeness degree is considered to have higher social network position diversity. This model captures whether a thread with a higher academic and vocational background diversity and/or higher social network position diversity is more likely to provide posts or comments that are longer (length of response), more positive (sentiment), and engaged with higher cognitive processes in the interaction (active/constructive/interactive levels) on average.

Background diversity is very strongly connected to English-language writing proficiency, reading proficiency, and speaking proficiency diversity (0.92, 0.87, 0.89). It is very weakly connected to highest degree, employment status, and current student status diversity (0.24, 012,0.14).

Social network position is very strongly connected to degree centrality and betweenness centrality diversity and very weakly connected to the closeness centrality diversity (0.96, 0.99, 0.16). Average interaction level is very strongly connected to the average Active-Constructive-Interactive level and length of response (0.73, 0.78). Unlike the average Active-Constructive-Interactive level and length of response, sentiment polarity is negatively and weakly related to interaction (-0.34).

The three latent variables of interest and their indicator variables are presented in Fig. 25. Background diversity very weakly predicts social network position diversity (0.30). Diversity of background cannot predict interaction (-0.03), which means that an increase in each indicator variable of background is not related to a change in the ACI level, length of response, or sentiment polarity.

A very weak and negative connection is found between social network position diversity and interaction (-0.18), which indicates that an increase in each indicator variable associated with social network position diversity is very weakly related to the increase in average ACI level and length of response and to the decrease of average sentiment polarity.

Background cannot predict the interaction level (-0.03). It indicated that whether a thread has learners with more diverse academic and vocational background does not predict the average interaction level of that thread.

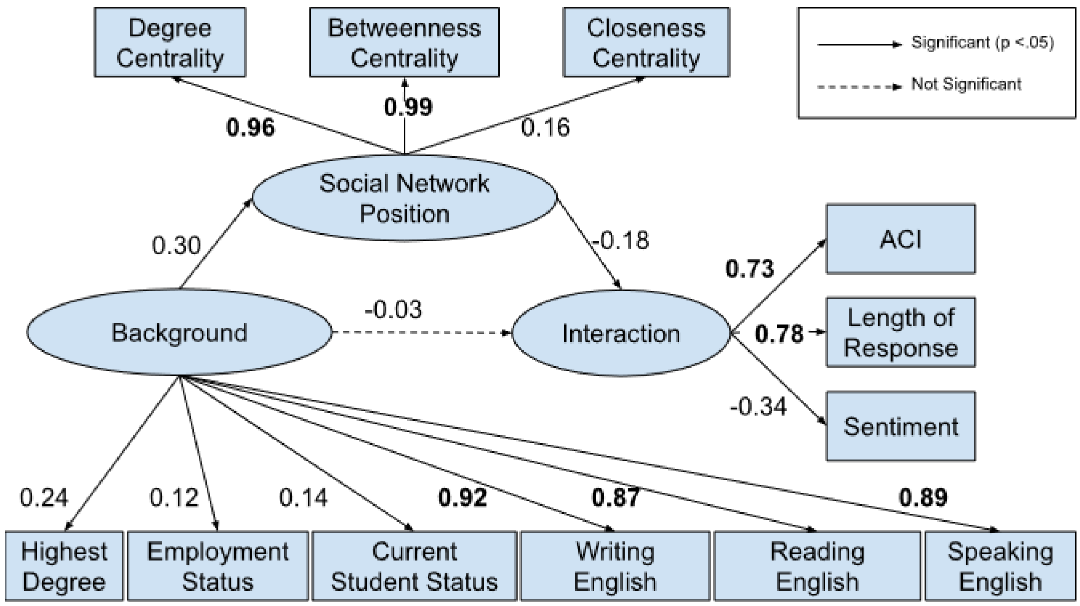

Figure 25. Contribution of thread diversity of background and social network position to thread interaction level for all threads.

Relationship for the top 20% threads with the highest ACI score

Unlike all the threads, background and social network position diversity of the top 20% of threads are very weakly and positively related to interaction. The contribution of background diversity (0.24) is stronger than that of social network position (0.14). However, background diversity does not contribute to social network position diversity for the top 20% of threads (Fig. 26).

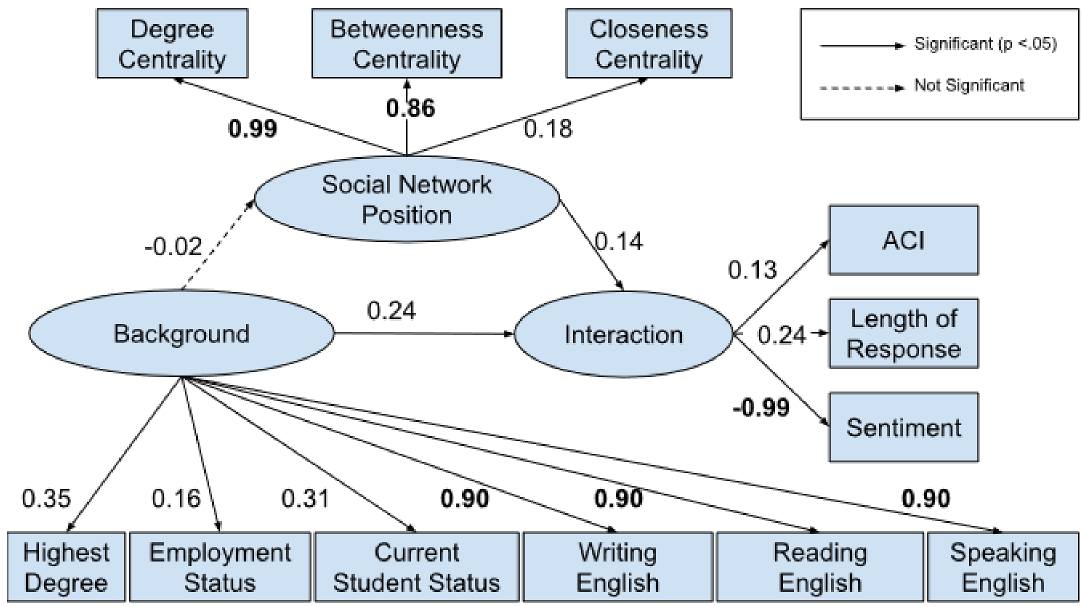

Figure 26. Contribution of thread diversity of background and social network position to the thread interaction level for the top 20% of threads with the highest ACI score.

Relationship for the bottom 20% threads with the lowest ACI score

The pattern observed among the bottom 20% of threads is not consistent with that of all threads or the top 20% of threads. The background and social network position diversity of the bottom 20% of threads is very weakly and negatively related to interaction (-0.13, -0.12). Finally, background diversity does not contribute to social network position diversity as it does for the top 20% of threads.

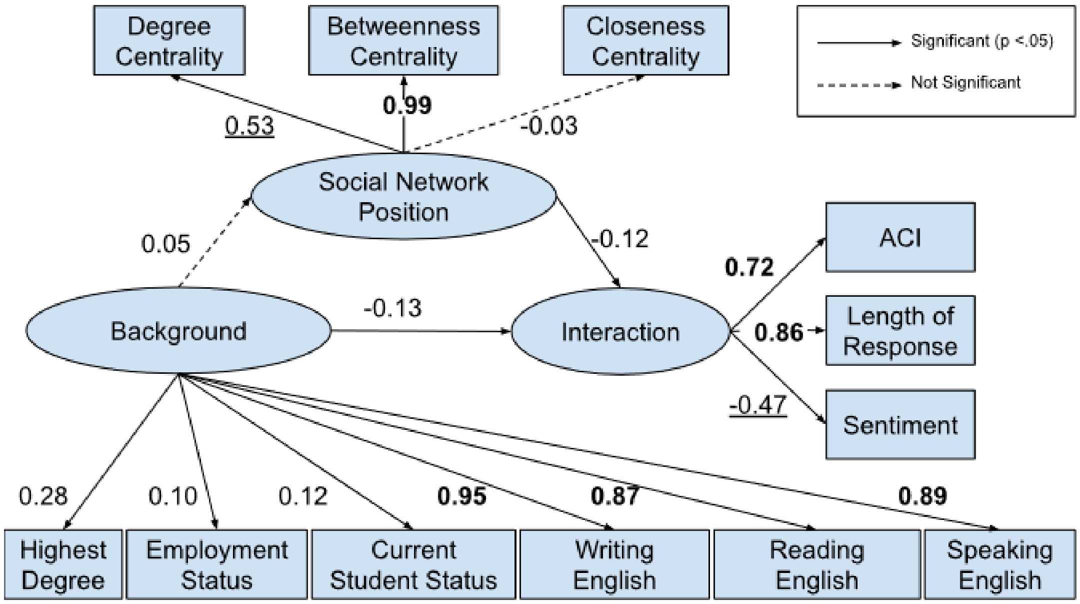

Figure 27. Contribution of thread diversity of background and social network position to thread interaction level for the bottom 20% of threads with the lowest ACI score.

Summary of research question 2

As with the pattern found among individual learners, the relationship pattern among background, social network position, and interaction is inconsistent for threads with different levels of diversity. In general, the contribution of the thread diversity to interaction level is weaker than that of the individual average. For all threads, background diversity can very weakly predict social network position but not interaction. social network position can very weakly and negatively predict interaction. However, for the top 20% of threads with the highest ACI level, both background and social network position diversity are very weak and positive predictors of interaction. Meanwhile, background diversity is not a predictor of social network position diversity. For the bottom 20% of threads, very weak negative effects are found for both background and social network position diversity.

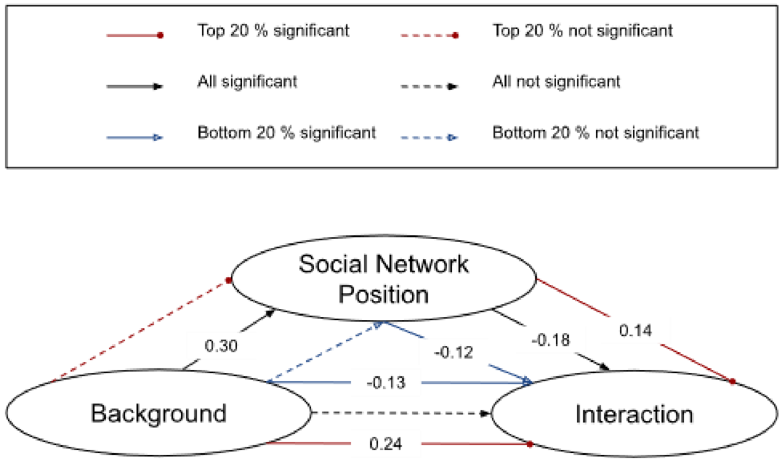

Figure 28. Relationship among thread diversity in background, social network position, and interaction

One thread from the top 20% and one from the bottom 20% are randomly selected from the discussion forum. A top 20% threads with highest average ACI is the thread 1559 (Table 12). It included 3 posts by Arnold and Lee (pseudonyms). Arnold is a male born in 1986 who has a bachelor's degree (e.g., BA, AB, BS). He is not a current student, is employed full-time (35 or more hours per week), his writing and speaking English is sufficient for most situations, and his reading English proficiency is native English speaker or equivalent. Arnold's standardized degree centrality, betweenness centrality and closeness centrality are 0.0054, 0.0000, and 0.0013 correspondingly, which are greater than 31.4%, 0.0%, and 16.2% learners.

Table 12. Content, length, sentiment and level of posts and comments of thread 1559.

Name	**Text**	**Length**	**Sentiment**	**ACI**
Arnold	Hi Coursera Members,I'm personally interested in the project of applying what we've learnt here into solving one of the big problems in cities around the world : Traffic Jam. I'm living in	105	0.35	C

	Bangkok. It is notorious for its standstill traffic jams that could last for hours. As we are having more and more Metropolitan areas around the world, this problem will become more and more prevalent. In solving this, we could improve the living quality of people more by liberating them from traffic jams thus giving them more quality time in life. Are you interested to join me on my adventure? If you do have any advice or words of wisdom, please do share it with us			
Arnold	Dear Bambardekar,I hope I'm addressing you correctly. Thank you very much for your input. I really appreciate it. Dear Herrera,I hope I"m addressing you correctly. I've actually read a similar system being implemented by IBM in a country before. It will actually measure the traffic flow into the city and it will charge accordingly. In other words, IBM was trying to regulate traffic through economical ways. When the traffic is busy, people that really don't need to travel to the city will make decisions to go into the city in another time. Where are you from? Is traffic very bad in your place? I believe traffic jams is a complex problems that	124	0.04	I

	needed to be solved from different perspectives. Traffic jams in different countries might face different bottlenecks. I'd love to hear from you more.			
Lee	Hi,Today I was actually thinking about the same topic. Although my approach was more like using sensors and intelligent systems to control the way traffic lights work, I would really enjoy hearing about different alternatives to solve the problem. Needless to say, I'm really interested in this project.	45	0.18	C

Lee is a male born in 1993 who has some college but no degree. He is a current student, is unemployed and looking for work, his writing and speaking English is sufficient for most situations, and his reading English proficiency is native English speaker or equivalent. Lee's standardized degree centrality, betweenness centrality and closeness centrality are 0.0027, 0.0000, and 0.0013 correspondingly, which are greater than 7.8%, 0.0%, and 16.2% learners.

A bottom 20% threads with lowest average ACI is the thread 1348 (Table 13) It includes 2 posts left by Nat and Val (pseudonyms). Nat is a male born in 1984, he has a master's degree (e.g., MA, MS, MEng, MEd, MSW, MBA). He is not a current student, is employed full-time (35 or more hours per week), his writing, reading and speaking English proficiency is native English speaker or equivalent. Nat's standardized degree centrality, betweenness centrality and closeness centrality are 0.0110, 0.0010, and 0.1918 correspondingly, which are greater than 54.7%, 73.2%, and 38.9% learners.

Table 13. Content, length, sentiment and level of posts and comments of thread 1348.

Name	Text	Length	Sentiment	ACI
Nat	Hi Cristina,I am interested in your idea and would like to contribute via my expertise as IT engineer and interested in the information visualization domain. Let us see how we can collaborate.BTW, currently, I am based in Berlin.Best,Selim	38	0.17	A
Val	Hi Cristina,you might want to look into audio entrainment. There are a bunch of channels on youtube that you might find inspiring. Some examples:http://www.youtube.com/user/AudioEntrainment http://www.youtube.com/user/voffvonuggla http://www.youtube.com/user/MrKlawdek http://www.youtube.com/user/projectvampireTV	25	0.50	A

Val is a male born in 1971, he has a bachelor's degree (e.g., BA, AB, BS). He is not a current student, is employed full-time (35 or more hours per week), his writing, reading and speaking English proficiency. Val’s standardized degree centrality, betweenness centrality and closeness centrality are 0.0014, 0.0000, and 0.0000 correspondingly, which are greater than 7.8%, 0.0%, and 0.0% learners.

Arnold and Lee have different highest degree, current student status, and employment status. Nat and Val have different highest degree and English-language proficiency (writing/reading/speaking English). They all have different levels of social network position. The thread variance can be seen in Table 14. No pattern can be seen from two examples here, which validates the very weak relationship between diversity and interaction.

Table 14. Variance of background and social network position for thread 1559 and 1348.

ID	Highest Degree	Current Student	Employ	Write	Read	Speak	Degree	Between	Close
1559	0.5	2.0	2.0	0.0	0.0	0.0	0.000004	0.0	0.0
1348	0.5	0.0	0.0	0.5	0.5	0.5	0.000046	0.0	0.018398

Again, since the model captures statistically significant features for all the observations in the dataset, the features from the 2 specific examples provided here are only for demonstration purpose. They do not imply any conclusions that go beyond the models.

Summary of Results

Fig. 29 indicates that the relationships of background, social network position, and interaction for different subgroups are inconsistent. Compared to all the other indicators of background, English-language proficiency is always associated more closely with background. Degree centrality and betweenness centrality diversity are strongly associated with social network position. However, closeness centrality only often has a weaker association. Sentiment polarity is negatively associated with interaction and its indicators in general, including ACI score and length of response.

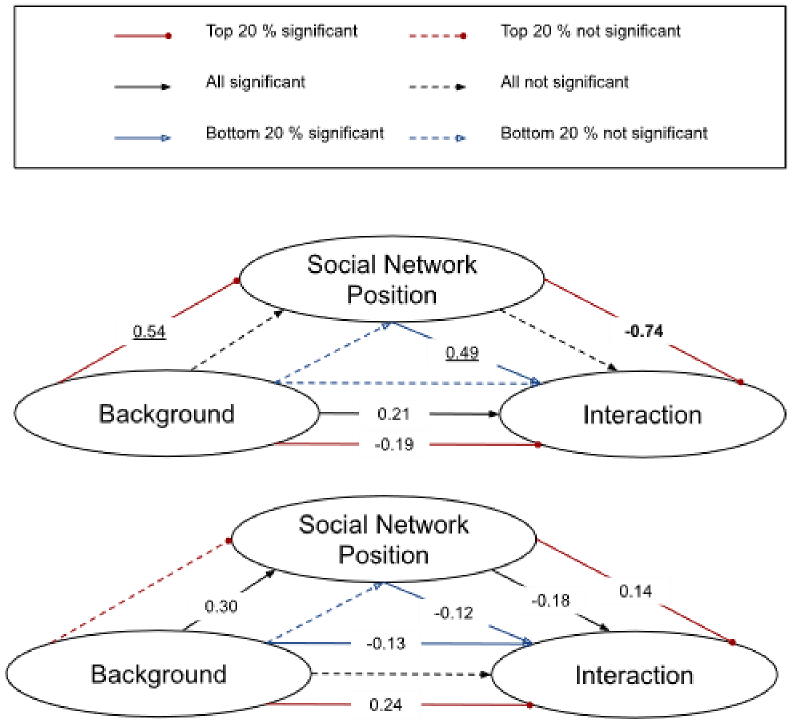

Figure 29. Comparison between individual average and thread diversity.

At the individual level, background weakly contributes to interaction for all learners. Although there is no significant contribution of social network position for all the learners, the top 20% and bottom 20% of learners with higher social network position tend to have more constructive activities.

It is obvious that the connections for individual learners are stronger in general compared to thread diversity. For all the threads, background diversity can positively predict social network position diversity but has no association with interaction level. For both the top 20% and bottom 20% of threads, background diversity does not contribute to social network position; however, it is weakly associated with interaction to a different extent.

On the other hand, social network position diversity is weakly and negatively associated with interaction for all the threads. The relationship between social network position and interaction follows the same pattern for the lower 20% of threads. For the top 20%, social network position positively predicts interaction.

Chapter 5

DISCUSSION AND CONCLUSION

In this chapter, the results presented in Chapter 4 are summarized in relation to the research questions investigated in this study. A discussion of the results' implications, as well as the conclusion to the study, are also found in this chapter.

Overview

The influence of background information and of social network position on MOOC interaction are often discussed separately. Some studies have focused on the effects of background. The influence of a learner's highest degree, employment status, current student status, and English-language proficiency have been considered independently of one another (Cho & Byun, 2017; DeBoer et al., 2013; Gillani & Eynon, 2014; Tong, & Li, 2018). Other studies have discussed social network position and its influence on interaction. Using social network analysis, de Lima and Zorrilla (2017) found that the interaction among learners enrolled in a social MOOC was limited and teacher-centered. Schaffer et al. (2016) found that 35% of learners never connected to anyone else in their social network and had a significantly higher dropout rate than learners who did. If a learner had connected with someone, he or she was twice as likely to start a conversation again.

The aforementioned studies consider the density of social networks and the frequency of interaction without investigating the nature and depth of interaction using the content analysis. In this dissertation, I analyzed the relationship among background, social network, and interaction, and compared the factors of background and social network to see which influenced interaction the most. Instead of investigating only the frequency of interaction, this study considered the nature and depth of the interaction by classifying posts and comments according to the ACI model. This study also investigated the different patterns of relationships found in the top 20% and bottom 20% subgroups.

Research Question 1: From the perspective of the individual learner, how does one's background and social network position affect one's interaction?

Our first study investigated the relationship among background, social network position, and interaction at the individual level. The relationship patterns of all learners, the top 20% of students with the highest average ACI scores, and the bottom 20% of learners with the lowest ACI scores were compared.

Indicators of interaction

At the individual level, interaction was always strongly and positively associated with ACI scores (0.71). Even when the length of the response and the response's sentiment did not contribute to interaction for the top 20% (-0.11, 0.02) and bottom 20% of learners (0.11, 0.01), the ACI level was still closely associated with interaction. This indicates that the ACI level is a component that reliably reflects the nature and depth of interaction.

Length of response was strongly associated with interaction for all learners (0.72), but it had no connection to interaction for either the top 20% or bottom 20% of learners (0.02, 0.01). For learners with extreme ACI scores, length of response did not contribute to the quality of interaction, which indicated the longer responses were not necessarily the ones with higher ACI. One possible explanation for this is that length of response was moderately correlated with ACI level (0.49, $p < 0.001$). The top 20% of learners all tended to leave longer posts and comments and had ACI scores greater than 2. The range of lengths, as determined by word count, may thus have been narrow, making differentiation with a similarly narrow range of ACI scores impossible. A similar reason may explain the bottom 20%.

Nisbet (2004) investigated the relationship among the word count of each posting, number of postings and stages of interaction according to a 5-stage framework (Salmon, 2000). The researcher found that the word count of postings is strongly correlated with the number of postings, which is clear evidence of the motivation to making connections. Meanwhile, it moderately correlated with the stage of interaction, the longest postings tend to be stage 4, knowledge construction, while few postings reached state 5, development (Nisbet, 2004). This conclusion is consistent with the current study. This study also demonstrated that the longer posts or comments were associated to a higher ACI interaction level, which all have constructive component.

For all the learners, sentiment polarity was negatively associated with interaction, as well as with length of response and ACI. In other words, longer posts and comments with higher ACI levels often demonstrated a mildly negative sentimental tone. Sentiment is an important predictor of the dropout rate (Schmidt & McCormick, 2013; Ramesh, Goldwasser, Huang, Daume, & Getoor, 2014; Wen, Yang, & Rose, 2014) and performance (Hone & El Said, 2016; Tucker, Dickens, & Divinsky, 2014) in MOOCS. Sentiment is not always positively correlated with interaction, however; a learner who is highly engaged in an interaction may also have many posts that express negative sentiment (Ramesh, Goldwasser, Huang, Daumé, & Getoor, 2013; Wen, Yang, & Rose, 2014). Our research demonstrates that negative sentiment tends to occur with longer and higher levels of interaction.

Unlike the instructors whose sentiment tend to always be positive, it it very common for learners to show neutral or negative sentiment in a learning context (Kagklis, Karatrantou, Tantoula, Panagiotakopoulos, & Verykios, 2015). The negative sentiment can be brought by the difficulty of problems (Kagklis, Karatrantou, Tantoula, Panagiotakopoulos, & Verykios, 2015), which is positively correlated to the student's performance especially for those who have a higher cognitive ability (Latham, Seijts, & Crim, 2008). This study also observed the more negative sentiment among the learners whose interaction involves in higher cognitive process (constructive or interactive), they showed a better ability for to provide high quality feedback even with negative sentiment.

Background and its contribution to interaction

For all the learners, background weakly predicted interaction, indicating that an increase in all of the significant indicators of a learner's background leads to an increase in the learner's ACI score and length of response and a decrease in the learner's sentiment polarity.

Highest degree was weakly associated with interaction. As indicated by prior research, the majority of MOOC learners have a bachelor's degree, followed by a master's degree (DeBoer, Stump, Seaton, & Breslow, 2013); the same pattern was found in this study. DeBoer et al. (2013) indicated that MOOC learners' highest degrees could positively predict their performance. By studying learners with doctorates in science and engineering, DeBoer et al. showed that the doctorate-achieving learners had the highest mean score, while learners with primary/secondary degrees had the lowest mean score. The current study expands on this line of research, demonstrating that a higher educational degree (0.21) is very weakly and positively associated with a learner's cognitive engagement level during interaction as well as his or her length of response. However, it is negatively associated with sentiment polarity (-0.29). In addition to their low level of representativeness and competitiveness in performance, learners with lower degrees did not show higher levels of cognitive engagement during interaction, although they did have a greater likelihood of having interactions with positive sentiment.

The extent to which employment status was associated with background and predicted interaction was similar to that of highest degree. Unemployment has been found to be positively associated with the demand of MOOCs (Tong, & Li, 2018); however, in the current study, this demand did not drive learners to higher levels of cognitive engagement during interaction. The positive relationship between employment status and interaction indicates that learners working more hours tend to have higher levels of cognitive engagement during their learning interactions.

Current student status did not consistently contribute to background. It either negatively contributed (the top 20% of learners with highest ACI scores) or did not contribute at all (all other learners). For the top 20% of learners with the highest ACI scores, current student status was the only positive indicator among all the background indicators that were associated with interaction. Among the learners who consistently engaged in high-level interaction (ACI scores), full-time students had even higher ACI levels than part-time students and non-students.

Writing, reading, and speaking English-language proficiency had a generally large and positive contribution to background. Learners' levels of proficiency in English influenced the frequency of and their preferences for interaction. Native English speakers in Europe and North America interact more actively on forums than non-native speakers from Asia (Gillani & Eynon, 2014). Non-native speakers prefer to have face-to-face interaction (Cho & Byun, 2017). The current study demonstrated that, in addition to the frequency of and preferences for interaction, the level of interaction, length of response, and sentiment polarity are influenced by learners' levels of proficiency in English. English proficiency is the strongest predictor of all the background indicators.

Social network position and its contribution to interaction

Degree centrality contributed most strongly to social network position, followed by betweenness centrality and then closeness centrality. Betweenness also contributed very strongly to social network position. This indicates that bridging connections among peers (betweenness centrality) contributes just like connecting to more peers does (degree centrality). Closeness centrality contributed the least to interaction. One possible explanation for this is that the social network of a MOOC discussion forum is very sparse. Learners are not generally close to their peers; therefore, closeness cannot effectively differentiate among MOOC learners.

Social network position could not predict interaction for all learners. However, among top performers, social network position very strongly and negatively predicted (-0.74) interaction. The top learners who connected more with other users tended to post or comment at lower levels. Since the average score for all the learners in this group was higher than 2 (constructive; see Fig. 20), the lower level for the top learners was the constructive level. For the bottom 20% of performers, social network position could fairly and positively predict (0.49) interaction (Fig. 23). The learners who connected and bridged more with other users tended to leave posts or comments at higher levels. Since the average score for all the learners in this group was less than 2 (constructive; see Fig. 22), the higher level for the bottom learners was also the constructive level.

Superposters commonly perform better than average learners and have lower dropout rates (Balakrishnan & Coetzee, 2013; Wong, Pursel, Divinsky, & Jansen, 2015). The threads in which they actively participate tend to have more views, replies, and votes and to last longer (Wong, Pursel, Divinsky, & Jansen, 2015). The number of connections (degree centrality) is often used as a measurement of social network position (Ergün & Usluel, 2016; Wong, Pursel, Divinsky, & Jansen, 2015). Online learners who connect with more peers contribute more high-quality and innovative ideas (Björk & Magnusson, 2009). These studies all discussed the performance of each learner independently, the high quality interaction does not necessary come from other peers' contribution. For example (Björk, & Magnusson, 2009) found that people with higher social network centrality tend to generate conversations that are more original and innovative, however, these original and innovative ideas may or may not ignore other's contribution.

Research Question 2: From the perspective of learners interacting in a thread, how does the thread's background and social network position diversity affect the thread's average interaction level?

Indicators of interaction

As it was for individual learners, interaction at the thread level was generally positively associated with ACI level (0.73) and length of response (0.78). It was negatively associated with sentiment polarity (-0.34). The thread interaction is the average of individual interaction traits; it is thus reasonable that it has generally similar patterns.

The bottom 20% of threads demonstrated similar patterns between interaction and its indicators. The interaction of the top 20% of threads had little connection to ACI (-0.13) and a weak connection to length of response (0.24). Interaction was strongly and negatively associated with sentiment polarity. When the interaction level was high, background diversity and social network diversity tended to occur with a decrease in the number of words used in the posts and comments.

Background diversity and its contribution to interaction

For all of the threads, background diversity could predict the social network position but not the interaction. In general, if learners who interacted in a thread had different backgrounds as compared to each other, their social network centralities tend to also be different. However, this does not necessarily associate to a higher average interaction level.

Background diversity is always observed among MOOC learners. Multiple studies have indicated that MOOC learners are diverse in terms of a number of background characteristics (DeBoer, Stump, Seaton, & Breslow, 2013; Mackness, Mak, & Williams, 2010; Schmidt & McCormick, 2013). Researchers have different attitudes towards the diversity observed among MOOC learners. DeBoer et al. (2013) and Mackness et al. (2010) argued an increase in diversity could potentially lead to learning limitations brought about by the lack of structure, support, and moderation. Diversity makes it hard to meet the needs of and provide support to online learners (Darken & Sibert, 1996; Salmon, 2004), thereby impairing performance. On the other hand, Schmidt and McCormick (2013) demonstrated both the challenging and rewarding aspects of diversity. Diversity inevitably increases the workload for instructors who had to solve problems for students with different levels of experience; however, the researchers observed more informative conversations and intense debates in a diverse course than in the same course taught on campus. In this study, no strong relationship is found between the diversity and the level of interaction.

The current study found no significant negative contribution of background diversity in any of the threads. Background diversity only impaired interaction very weakly (-0.13) if the average interaction level of a thread was low. For the top 20% of threads with the highest ACI scores, background diversity very weakly and positively contributed to the interaction level. This study focused on peer-to-peer interaction and eliminated any feedback provided by instructors.

Therefore, this study was unable to demonstrate whether diversity actually increased the workload of instructors, which has been considered a disadvantage in many other studies (Darken & Sibert, 1996; DeBoer et al., 2013; Mackness et al., 2010; Salmon, 2004; Schmidt & McCormick, 2013). It also was unable to conclude that diversity of background harms the quality and length of interaction.

Social network position diversity and its contribution to interaction

High levels of diversity in social network position are very common for MOOC discussion forums. The majority of MOOC learners usually leave only a few posts or comments with no replies (Schaffer et al., 2016); only a small group of active users contributes regularly to interaction (de Lima & Zorrilla, 2017; Wong, Pursel, Divinsky, & Jansen, 2015). Thread level diversity has also been reported by researchers. Ergün and Usluel (2016) found that active learners who have higher degree centrality are more likely to start a discussion in a thread, while learners with lower degree centrality tend to follow or remain quiet.

This study found the thread level diversity of social network position was very weakly predicted by diversity of background (0.30) If top learners who interacted in a thread had different social network position compared to each other, their average interaction level tends to be slightly higher. The thread level diversity of social network position also was negatively and weakly associated with interaction for all the threads and for the bottom 20% of threads with the lowest ACI scores. For all the learners other than the top 20%, if learners who interacted in a thread had different backgrounds compared to each other, their social network centralities tend to also be different. However, this does not necessarily associate to a higher average interaction level.This suggests that a thread with learners who have similar levels of connections with peers is slightly more likely to yield high-level interaction.

Implications

In practice, background and social network position could be associated with interaction, but MOOC instructors should be aware of the conditions that enable this to occur. Instructional plans encouraging learners to connect with their peers may lead to constructive activities but not interactive activities, the latter of which are based on peers' contributions. High levels of cognitive engagement in interaction are generally predicted by negative sentiment. Therefore, negative words are also significant components of interaction in higher-level cognitive engagement. This study reminds MOOC instructors that the posts and comments constructed by negative words are also worth noting. The English-language proficiency levels of individual learners strongly predicted interaction level. MOOCs usually attract a large number of learners whose native language is not English; these learners comprise a subgroup that merits greater attention.

High levels of diversity are inevitable for a platform like a MOOC that serves millions of learners. Prior research has examined whether diversity could lead to poor student support (Mackness, Mak, & Williams, 2010), recognizing that support is critical to the performance of online learners (Darken & Sibert, 1996; Salmon, 2004). This study demonstrated that diversity of background only weakly contributed to a decrease in interaction level for learners. Although negative, the effects of social network position diversity on interaction were generally weak. The top 20% of threads even showed a positive contribution of social network position diversity to interaction. Thread level diversity did not significantly impair interaction level.

The discussion forum is the primary form of peer-to-peer interaction for most MOOCs. Forums can accumulate hundreds of thousands of posts and comments, some of which are never read or replied to by any instructor or learner. Among the 829 users of the content-related forums examined in this study, 99 users created 111 threads that received no replies. This constitutes

10.6% of the total 1,047 threads. This course had six instructors and multiple teaching assistants, but the instructors and assistants were nevertheless unable to respond to all posts and comments or to evaluate the course interaction.

In this study, an automatic classification method was used to efficiently evaluate interaction. It was demonstrated that the automatic classification method can reach substantive agreement with a human rater (Cohen's kappa, 0.676) and classify a larger number of posts and comments (5,510 in our case) within a shorter period. The qualitative analysis of MOOC discussion forum could be time-consuming, this automatic classification method can generalize the result of qualitative analysis to a larger dataset. The results reflect the interaction levels of all the learners, which can be used as input for other research questions of interest.

The data analysis methods used in this research can also be embedded into the instructional design to provide real-time feedback about student's interaction. For example, the automatic classifier can efficiently provide the interaction level in a way that human instructors cannot finish in a short period. The social network analysis can also be used to identify the learner(s) in the periphery of the network.

Limitations

Auto-Classification

In this study, an auto-classification method was used to conduct the qualitative analysis of a large number of posts and comments. Although the classifier's performance reached substantive agreement with a human rater, it was inevitable that the classifier would introduce systematic error just like its human counterparts. The classifier is not perfectly precise in its understanding of the nuanced coding differences between interactive and constructive activities. For example, in one comment, a learner wrote:

A misunderstanding for sure. I understood your structure to expect the incumbent to struggle with that set of seemingly contradictory competencies, which may not be the case if one were to match the profile for this job with that of the incumbent. It's common practice for management to use profiling for this purpose so I'm not sure what it is that you're on about. The link is to share information pertaining to this. Don't bother replying and delete what you want.

This comment was rated as interactive by the human rater but as constructive by the classifier. The classifier captured the constructive activities in the semantic features; however, it did not capture that the commenter was building on another person's post since there was no name mentioned explicitly in the text. Therefore, it failed to classify the comment as an interactive activity. This raises questions about how to combine machine learning and human coding accurately.

Machine learning has long been used in education research. It can predict the performance, dropout rate, and sentiment in the learning context (Hu, Lo, & Shih, 2014; Li, Hoi, Chang & Jain, 2010; Minaei-Bidgoli, Kortemeyer, & Punch, 2004). It is also used to automate time-consuming human tasks in educational practice. It helps instructors to grade papers and exams for a large number of students within a short period of time, identify the critical assignment (Heys, 2018), identify the students' characteristics and performance (Chatterjee, Marachi, Natekar, Rai, & Yeung, 2018), and provide personalized feedback (Vie, Popineau, Bruillard, & Bourda, 2018). Just like any other human raters, machine learning cannot achieve a perfectly accurate performance.

Researchers usually make efforts to improve the accuracy by optimizing the data pre-processing, using more training data, and using different models (Le, Ngiam, Coates Lahiri, Prochnow & Ng, 2011). On the other hand, the misclassified observations can be used to provide further information. For example, Chatterjee et al. (2018) used a machine learning algorithm to predict whether a group of students can graduate. They then focused on misclassified students. They referred the students who the model predicted should have graduated but did not graduate as the 'potentially at-risk' group, and the students who the model believed should have failed to graduate but did graduate as the 'learning group'. The characteristics of these focus groups provide information for institutions to intervene in the students at-risk for favorable results. In this study, more time-consuming optimization could be applied for a more accurate model. A follow-up study to summarize the characteristics of the inaccurate predictions is also helpful for interpreting the machine learning results.

Sentiment Analysis

The word-based sentiment lexicon has been well-developed and is widely used in online social media sentiment analysis (Chaplot, Rhim, & Kim, 2015; Fong; 2017; Lubis, Rosmansyah, & Supangkat, 2016; Wen, Yang, & Rose, 2014). It can efficiently capture the sentiment polarity of posts and comments without time-consuming training; however, it is incapable of capturing phrase-, sentence-, or even paragraph-level sentiment. This could influence the accuracy of sentiment analysis, especially in a multivariate predictable model. More precise approaches are necessary for the further investigation of the sentiment polarity of interaction.

Conclusion

This research compared the magnitude and significance of factors influencing interaction, including background and social network position and their indicators. Prior research has largely focused on the effects of background and social network position on quantitative features of interaction, such as the number of views, replies, and votes, as well as the duration of threads. This research expanded the scope of the investigation to consider qualitative features such as cognitive engagement level (ACI score) and sentiment polarity in interaction. It also evaluated the extent to which each of these factors influences interaction.

The contributions of background and social network position to interaction were inconsistent across different subgroups. At the individual level, only background contributed to interaction. Of the various background indicators, English-language proficiency consistently contributed the most. Both the top and bottom 20% of learners in our dataset who actively connected to peers, bridged connections between peers, and were closer to their peers tended to engage in constructive activities, rather than active or interactive ones. This conclusion is drawn based on the subsets of this current dataset. Longer posts and comments often demonstrated higher levels of cognitive engagement and used more words with negative sentiment polarity.

The investigation of different subgroups revealed similarly inconsistent patterns for threads. Thread diversity was not as strong of a predictor as individual average. Only social network position diversity could very weakly and negatively predict interaction for all the threads, indicating that a thread constituted by learners connected to more of their peers and learners with fewer connections can create lower levels of interaction. For the top 20% of threads, the diversity of background neither contributed to nor impaired ACI and length of response. However, a thread with learners from diverse backgrounds had more negative words in its posts and comments. For the bottom 20% of threads, diversity of background only very weakly and negatively influenced interaction. In general, diversity did not impair interaction, as cautioned by other researchers.

Reference

Anderson, T. (2004). Towards a theory of online learning. *Theory and practice of online learning*, *2*, 109-119.

Anderson, C. (2004). The long tail. *Wired magazine*, *12*(10), 170-177.

Arguello, J., and Shaffer, K. (2015, April). Predicting Speech Acts in MOOC Forum Posts. In Ninth International AAAI Conference on Web and Social Media. Retrieved from http://www.aaai.org/ocs/index.php/ICWSM/ICWSM15/paper/view/10526

Balaji, H., Govindasamy, V., & Akila, V. (2016). Social opinion mining and concise rendition. Paper presented at the 641-645. Retrieved from http://ezaccess.libraries.psu.edu/login?url=https://search.proquest.com/docview/1862203683?accountid=13158

Balakrishnan, G., & Coetzee, D. (2013). *Predicting student retention in massive open online courses using hidden Markov models.* Berkeley: EECs Department, University of California.

Baturay, M. H. (2015). An overview of the world of MOOCs. *Procedia-Social and Behavioral Sciences*, *174*, 427-433.

Bayeck, R. Y., Hristova, A., Jablokow, K. W., & Bonafini, F. (2018). Exploring the relevance of single-gender group formation: What we learn from a massive open online course (MOOC). *British Journal of Educational Technology*.

Beaven, T., Hauck, M., Comas-Quinn, A., Lewis, T., & de los Arcos, B. (2014). MOOCs: Striking the right balance between facilitation and self-determination. *Journal of Online Learning and Teaching*, *10*(1), 31.

Ben-David, A. (2008). Comparison of classification accuracy using Cohen's Weighted Kappa. *Expert Systems with Applications*, *34*(2), 825-832.

Borgatti, S. P., Mehra, A., Brass, D. J., & Labianca, G. (2009). Network analysis in the social sciences. *science*, *323*(5916), 892-895.

Bozkurt, A., Honeychurch, S., Caines, A., Bali, M., Koutropoulos, A., & Cormier, D. (2016). Community tracking in a cMOOC and nomadic learner behavior identification on a connectivist rhizomatic learning network. *Turkish Online Journal of Distance Education, 17*(4), 27. Retrieved from http://ezaccess.libraries.psu.edu/login?url=https://search.proquest.com/docview/1871583167?accountid=13158

Branson, K. J. (2017). *Academic self-efficacy and massive open online course (MOOC) completion rates: Do academic self-efficacy and adult learner characteristics influence MOOC outcomes?*(Order No. 10640783). Available from ProQuest Dissertations & Theses A&I. (1988302843). Retrieved from http://ezaccess.libraries.psu.edu/login?url=https://search.proquest.com/docview/1988302843?accountid=13158

Breslow, L., Pritchard, D. E., Deboer, J., Stump, G. S., Ho, A., & Seaton, D. (2013). Studying Learning in the Worldwide Classroom: Research into edX's First MOOC. *Research & Practice in Assessment, 8*(March 2012), 13–25. Retrieved from http://www.rpajournal.com/studying-learning-in-the-worldwide-classroom-research-into-edxs-first-mooc/

Brown, J.S., & Adler, R. P. (2008). Open education, the long tail, and learning 2.0. *Educause review*, *43*(1), 16-20.

Bruff, D. (2013). Lessons learned from Vanderbilt's first MOOCs. *2013-10-17. http://cft, vanderbilt, edu/2013/08/lessons-learned-from-vanderbilts-first-moocs.*

Burt, R. S. (1978). Cohesion versus structural equivalence as a basis for network subgroups. *Sociological Methods & Research*, *7*(2), 189-212.

Carrington, P. J., Scott, J., & Wasserman, S. (Eds.). (2005). *Models and methods in social network analysis* (Vol. 28). Cambridge university press.

Castaño-Muñoz, J., Kreijns, K., Kalz, M., & Punie, Y. (2017). Does digital competence and occupational setting influence MOOC participation? Evidence from a cross-course survey. *Journal of Computing in Higher Education*, *29*(1), 28-46.

Carver, L., & Harrison, L. M. (2013). MOOCs and democratic education. *Liberal Education, 99*(4), 20. Retrieved from https://aacu.org/liberaleducation/2013/fall/carver- harrison.

Chaplot, D. S., Rhim, E., & Kim, J. (2015, June). Predicting Student Attrition in MOOCs using Sentiment Analysis and Neural Networks. In *AIED Workshops*.

Chatterjee, A., Marachi, C., Natekar, S., Rai, C., & Yeung, F. (2018). Using Logistic Regression Model to Identify Student Characteristics to Tailor Graduation Initiatives. *College Student Journal*, *52*(3), 352-360.

Chi, M. T., Adams, J., Bogusch, E. B., Bruchok, C., Kang, S., Lancaster, M., ... & Wylie, R. (2018). Translating the ICAP theory of cognitive engagement into practice. *Cognitive science*, *42*(6), 1777-1832.

Chi, M. T. (2009). Active-constructive-interactive: A conceptual framework for differentiating learning activities. *Topics in cognitive science*, *1*(1), 73-105.

Chiu, K. F. T., & Hew, K. F. T. (2017). Factors influencing peer learning and performance in MOOC asynchronous online discussion forum. *Australasian Journal of Educational Technology*.

Cho, M. H., & Byun, M. K. (2017). Nonnative English-Speaking Students' Lived Learning Experiences With MOOCs in a Regular College Classroom. *The International Review of Research in Open and Distributed Learning*, *18*(5).

Conole, G. (2016). MOOCs as disruptive technologies: strategies for enhancing the learner experience and quality of MOOCs. RED. Revista de Educación a Distancia, (50).

Conrad, D. (2014). Interaction and communication in online learning communities: toward an engaged and flexible future. In O. Zawacki-Richter and T. Anderson (Eds.), *Online distance education: Towards a research agenda* (pp. 381–402). Edmonton, AB: Athabasca University Press.

Costa-jussà, M. R., Formiga, L., Torrillas, O., Petit, J., & Fonollosa, J. A. R. (2015). A MOOC on approaches to machine translation. *The International Review of Research in Open and Distributed Learning*, *16*(6).

Cross, S., & Whitelock, D. (2017). Similarity and difference in fee-paying and no-fee learner expectations, interaction and reaction to learning in a massive open online course. *Interactive Learning Environments*, *25*(4), 439-451

Crossley, S., McNamara, D. S., Baker, R., Wang, Y., Paquette, L., Barnes, T., & Bergner, Y. (2015). *Language to completion: Success in an educational data mining massive open online class* International Educational Data Mining Society, e-mail: admin@educationaldataminingorg; Web site: http://wwweducationaldataminingorg. Retrieved from http://ezaccess.libraries.psu.edu/login?url=https://search.proquest.com/docview/1773221682?accountid=13158

De Laat, M., Lally, V., Lipponen, L., & Simons, R. J. (2007). Investigating patterns of interaction in networked learning and computer-supported collaborative learning: A role for Social Network Analysis. *International Journal of Computer-Supported Collaborative Learning*, *2*(1), 87-103.

de Lima, M., & Zorrilla, M. E. (2017). Social Networks and the Building of Learning Communities: An Experimental Study of a Social MOOC. *The International Review of Research in Open and Distributed Learning*, *18*(1).

De Nooy, W., Mrvar, A., & Batagelj, V. (2011). *Exploratory social network analysis with Pajek* (Vol. 27). Cambridge University Press.

DeBoer, J., Ho, A. D., Stump, G. S., & Breslow, L. (2014). Changing “course” reconceptualizing educational variables for massive open online courses. *Educational researcher, 43*(2), 74-84.

DeBoer, J., Stump, G. S., Seaton, D., & Breslow, L. (2013, June). Diversity in MOOC students’ backgrounds and behaviors in relationship to performance in 6.002 x. In *Proceedings of the sixth learning international networks consortium conference* (Vol. 4, pp. 16-19).

Deng, R., & Benckendorff, P. (2017). A contemporary review of research methods adopted to understand students’ and instructors’ use of massive open online courses (MOOCs). *International Journal of Information and Education Technology*, *7*(8), 601.

Dillahunt, T. R., Wang, B. Z., & Teasley, S. (2014). Democratizing higher education: Exploring MOOC use among those who cannot afford a formal education. *The International Review of Research in Open and Distributed Learning*, *15*(5).

Dowell, N. M., Skrypnyk, O., Joksimovic, S., Graesser, A. C., Dawson, S., GaĹˇevic, D., ... & Kovanovic, V. (2015). Modeling Learners' Social Centrality and Performance through Language and Discourse. *International Educational Data Mining Society*.

Downes, S. (2008). Places to go: Connectivism and connective knowledge. Innovate. *Journal of Online Education, 5*(1), 1–6. Retrieved from http://nsuworks.nova.edu/cgi/ viewcontent.cgi?article=1037&context=innovate.

Ebben, M., & Murphy, J. S. (2014). Unpacking MOOC scholarly discourse: A review of nascent MOOC scholarship. *Learning, Media and Technology, 39*(3), 328–345. http:// dx.doi.org/10.1080/17439884.2013.878352.

Ergün, E., & Usluel, Y. K. (2016). An Analysis of Density and Degree-Centrality According to the Social Networking Structure Formed in an Online Learning Environment. *Journal of Educational Technology & Society*, *19*(4).

Fan, X. (2017). *Scalable teaching and learning via intelligent user interfaces* (Order No. 10645819). Available from ProQuest Dissertations & Theses A&I. (1944373854). Retrieved from http://ezaccess.libraries.psu.edu/login?url=https://search.proquest.com/docview/1944373854?accountid=13158

Fong, J. (2017). Sentiments and perspectives of academics about massive open online courses (MOOCs). *Journal on Excellence in College Teaching*, *28*(1), 49-76. Retrieved from http://ezaccess.libraries.psu.edu/login?url=https://search.proquest.com/docview/1913353421?accountid=13158

Harvey, L. A., Glinsky, J. V., Lowe, R., & Lowe, T. (2014). A massive open online course for teaching physiotherapy students and physiotherapists about spinal cord injuries. *Spinal Cord*, *52*(12), 911-8. http://dx.doi.org/10.1038/sc.2014.174

Heys, J. J. (2018). Machine Learning as a Tool to Identify Critical Assignments. *Chemical Engineering Education (CEE)*, *52*(4), 243-250.

Hone, K. S., & El Said, G. R. (2016). Exploring the factors affecting MOOC retention: A survey study. *Computers & Education*, *98*, 157-168.

Hu, Y. H., Lo, C. L., & Shih, S. P. (2014). Developing early warning systems to predict students' online learning performance. *Computers in Human Behavior*, *36*, 469-478.

Hung, B. W. K. (2017). *A graph-based, systems approach for detecting violent extremist radicalization trajectories and other latent behaviors* (Order No. 10602953). Available from ProQuest Dissertations & Theses A&I. (1961606266). Retrieved from http://ezaccess.libraries.psu.edu/login?url=https://search.proquest.com/docview/1961606266?accountid=13158

Garrido, M., Koepke, L., Andersen, S., Mena, A. F., Macapagal, M., & Dalvit, L. (2016). An examination of MOOC usage for professional workforce development outcomes in Colombia, the Philippines, & South Africa. *Seattle: Technology & Social Change Group, University of Washington Information School*.

Gasevic, D., Kovanovic, V., Joksimovic, S., & Siemens, G. (2014). Where is research on massive open online courses headed? A data analysis of the MOOC Research Initiative. *The International Review of Research in Open and Distributed Learning*, *15*(5).

Gillani, N., & Eynon, R. (2014). Communication patterns in massive open online course. *Internet and Higher Education*, *23*, 18–26.

Garrison, D. R., & Cleveland-Innes, M. (2005). Facilitating cognitive presence in online learning: Interaction is not enough. *The American Journal of Distance Education, 19*(3), 133–148.

Goodyear, P., Jones, C., & Thompson, K. (2014). Computer-supported collaborative learning: Instructional approaches, group processes and educational designs. In J. M. Spector, M. D. Merrill, J. Elen, & M. J. Bishop (Eds.), *Handbook of research on educational communications and technology* (4th ed., pp. 439–453). New York: Springer.

Goggins, S. P., Galyen, K. D., Petakovic, E., & Laffey, J. M. (2016). Connecting performance to social structure and pedagogy as a pathway to scaling learning analytics in MOOCs: An exploratory study. *Journal of Computer Assisted learning, 32*(3), 244–266.

Granovetter, M. S. (1983). The strength of weak ties: A network theory revisited. Sociological Theory, 1, 210–233. doi: 10.2307/202051

Guàrdia, L., Maina, M., & Sangrà, A. (2013). MOOC design principles: A pedagogical approach from the learner's perspective. *eLearning Papers*, (33).

Gunawardena, C. N., Lowe, C. A., & Anderson, T. (1997). Analysis of a global online debate and the development of an interaction analysis model for examining social construction of knowledge in computer conferencing. *Journal of educational computing research*, *17*(4), 397-431.

Hmedna, B., El Mezouary, A., Baz, O., & Mammass, D. (2017). Identifying and tracking learning styles in MOOCs: A neural networks approach. *International Journal of Innovation and Applied Studies*, *19*(2), 267.

Hone, K. S., & El Said, G. R. (2016). Exploring the factors affecting MOOC retention: A survey study. *Computers & Education*, *98*, 157-168.

Jackson, D. L. (2003). Revisiting sample size and number of parameter estimates: Some support for the N: q hypothesis. Structural Equation Modeling, 10(1), 128-141.

Jackson, M. (2014, October 5). *MOOCs, participation, and the Long Tail*. Retrieved from http://michelejackson.blogs.wm.edu/2014/10/05/moocs-participation-and-the-long-tail/

Jacoby, J. (2014). The disruptive potential of the massive open online course: A literature review. *Journal of Open Flexible and Distance Learning*, *18*(1), 73–85. Retrieved from http://files.eric.ed.gov/fulltext/EJ1079845.pdf.

Johnson, D., & Johnson, R. (2008). Cooperation and the use of technology. In J. M. Spector, M. D. Merrill, J. van Merrienboer, & M. Driscoll (Eds.), Handbook of research on educational communications and technology (3rd ed., pp. 659–670). New York: Routledge.

Joksimović, S., Dowell, N., Poquet, O., Kovanović, V., Gašević, D., Dawson, S., & Graesser, A. C. (2018). Exploring development of social capital in a CMOOC through language and discourse. *The Internet and Higher Education*, *36*, 54-64.

Kagklis, V., Karatrantou, A., Tantoula, M., Panagiotakopoulos, C. T., & Verykios, V. S. (2015). A learning analytics methodology for detecting sentiment in student fora: A case study in Distance Education. *European Journal of Open, Distance and E-learning*, *18*(2), 74-94.

Kaplan, A. M., & Haenlein, M. (2016). Higher education and the digital revolution: About MOOCs, SPOCs, social media, and the Cookie Monster. *Business Horizons*, *59*(4), 441-450.

Kellogg, S., Booth, S., & Oliver, K. (2014). A social network perspective on peer supported learning in MOOCs for educators. *The International Review of Research in Open and Distributed Learning*, *15*(5).

Kloft, M., Stiehler, F., Zheng, Z., & Pinkwart, N. (2014). Predicting MOOC dropout over weeks using machine learning methods. In *Proceedings of the EMNLP 2014 Workshop on Analysis of Large Scale Social Interaction in MOOCs* (pp. 60-65).

Kreijns, K., Kirschner, P. A., & Jochems, W. (2003). Identifying the pitfalls for social interaction in computer-supported collaborative learning environments: a review of the research. *Computers in human behavior*, *19*(3), 335-353.

Latham, G. P., Seijts, G., & Crim, D. (2008). The effects of learning goal difficulty level and cognitive ability on performance. *Canadian Journal of Behavioural Science/Revue canadienne des sciences du comportement*, *40*(4), 220.

Lave, J., & Wenger, E. (1991). *Situated learning: Legitimate peripheral participation*. Cambridge university press.

Lazarsfeld, P. F., Berelson, B., & Gaudet, H. (1944). The people's choice.

Li, G., Hoi, S. C., Chang, K., & Jain, R. (2010, December). Micro-blogging sentiment detection by collaborative online learning. In *2010 IEEE International Conference on Data Mining* (pp. 893-898). IEEE.

Liu, W., Sidhu, A., Beacom, A. M., & Valente, T. W. (2017). Social network theory. *The International Encyclopedia of Media Effects*.

Liyanagunawardena, T. R., Adams, A. A., & Williams, S. A. (2013). MOOCs: A systematic study of the published literature 2008-2012. *The International Review of Research in Open and Distributed Learning, 14*(3), 202-227.

Loizzo, J., & Ertmer, P. A. (2016). MOOCocracy: the learning culture of massive open online courses. *Educational Technology Research and Development*, *64*(6), 1013-1032.

Lubis, F. F., Rosmansyah, Y., & Supangkat, S. H. (2016). Experience in learners review to determine attribute relation for course completion. Paper presented at the 32-36. Retrieved from http://ezaccess.libraries.psu.edu/login?url=https://search.proquest.com/docview/1855468685?accountid=13158

Major, C. H., & Blackmon, S. J. (2016). Massive Open Online Courses: Variations on a new instructional form. *New Directions for Institutional Research*, *2015*(167), 11-25.

Mackness, J., Mak, S., & Williams, R. (2010). The ideals and reality of participating in a MOOC. In *Proceedings of the 7th international conference on networked learning 2010* (pp. 266-275). University of Lancaster.

Manning, J., & Sanders, M. (2013). How widely used are MOOC forums? A first look. Retrieved from https://www.stanford.edu/dept/vpol/cgi-bin/wordpress/how-widely-used-are-mooc-forums-a-first-look/

McAuley, A., Stewart, B., Siemens, G., & Cormier, D. (2010). The MOOC model for digital practice (CC attribution) Retrieved from http://www.elearnspace.org/Articles/MOOC_Final.pdf.

Meek, S. E. M., Blakemore, L., & Marks, L. (2017). Is peer review an appropriate form of assessment in a MOOC? student participation and performance in formative peer review.

Assessment and Evaluation in Higher Education, 42(6), 1000-1013. http://dx.doi.org/10.1080/02602938.2016.1221052

Minaei-Bidgoli, B., Kortemeyer, G., & Punch, W. F. (2004, August). Enhancing Online Learning Performance: An Application of Data Mining Methods. In *CATE* (pp. 173-178).

Mishra, D., Cayzer, S., & Madden, T. (2017). Tutors and gatekeepers in sustainability MOOCS. *On the Horizon*, *25*(1), 45-59. Retrieved from http://ezaccess.libraries.psu.edu/login?url=https://search.proquest.com/docview/1865399721?accountid=13158

Moore, M., & Kearsley, G. (1996). Distance education: A systems view. Belmont: Wadsworth.

Moreno, J. L. (1934). Who Shall Survive? Nervous and Mental Disease.

Nesterko, S. O., Dotsenko, S., Han, Q., Seaton, D., Reich, J., Chuang, I., & Ho, A. D. (2013, December). Evaluating the geographic data in MOOCs. In *Neural information processing systems*.

Neuböck, K., Kopp, M., & Ebner, M. (2015, May). What do we know about typical MOOC participants? First insights from the field. In *Proceedings of eMOOCs 2015 conference* (pp. 183-190).

Nisbet, D. (2004). Measuring the quantity and quality of online discussion group interaction. *Journal of eLiteracy*, *1*(2), 122-139.

Nkuyubwatsi, B. (2014). Cultural translation in massive open online courses (MOOCs). *eLearning Papers, 37,* 23–32. Retrieved from https://lra.le.ac.uk/bitstream/2381/28554/1/Cultural%20translation%20in%20MOOC%20Edited.pdf.

Nurmela, K., Lehtinen, E., & Palonen, T. (1999). Evaluating CSCL log files by social network analysis. Proceedings of CSCL 1999 (December 1999), Palo Alto, CA

Oakley, B., Poole, D., & Nestor, M. (2016). Creating a Sticky MOOC. *Online Learning*, *20*(1), 13-24.

Otte, E., & Rousseau, R. (2002). Social network analysis: a powerful strategy, also for the information sciences. *Journal of information Science*, *28*(6), 441-453.

Palin, A. (2014). Moocs: Young students from developing countries are still in the minority. *Financial Times*.

Paquette, G., Mariño, O., Rogozan, D., & Léonard, M. (2015). Competency-based personalization for massive online learning. *Smart Learning Environments*, *2*(1), 4.

Perna, L. W., Ruby, A., Boruch, R. F., Wang, N., Scull, J., Ahmad, S., & Evans, C. (2014). Moving through MOOCs: Understanding the progression of users in massive open online courses. *Educational Researcher*, *43*(9), 421-432.

Phipps, R., & Merisotis, J. (1999). What's the difference? A review of contemporary research on the effectiveness of distance learning in higher education.

Pillutla, V. S. S. (2017). *Helping users learn about social processes while learning from users: Developing a positive feedback in social computing* (Order No. 10264539). Available from ProQuest Dissertations & Theses A&I. (1919002570). Retrieved from http://ezaccess.libraries.psu.edu/login?url=https://search.proquest.com/docview/1919002570?accountid=13158

Ramesh, A., Goldwasser, D., Huang, B., Daume, H., & Getoor, L. (2014). Understanding MOOC discussion forums using seeded LDA. In *Proceedings of the ninth workshop on innovative use of NLP for building educational applications*(pp. 28-33).

Ramesh, A., Goldwasser, D., Huang, B., Daumé, H., & Getoor, L. (2013). Modeling learner engagement in MOOCs using probabilistic soft logic. In *NIPS Workshop on Data Driven Education* (Vol. 21, p. 62).

Reeves, T. D., & Pedulla, J. J. (2011). Predictors of teacher satisfaction with online professional development: Evidence from the USA's e-Learning for Educators initiative. Professional Development in Education, 37(4), 591–611.

Reffay, C., & Chanier, T. (2003). How social network analysis can help to measure cohesion in collaborative distance-learning. In *Designing for change in networked learning environments* (pp. 343-352). Springer, Dordrecht.

Robinson, C., Yeomans, M., Reich, J., Hulleman, C., & Gehlbach, H. (2016, April). Forecasting student achievement in MOOCs with natural language processing. In *Proceedings of the Sixth International Conference on Learning Analytics & Knowledge* (pp. 383-387). ACM.

Roschelle, J., & Teasley, S. D. (1995). The construction of shared knowledge in collaborative problem solving. In *Computer supported collaborative learning* (pp. 69-97). Springer, Berlin, Heidelberg.

Ryan, L. (2013). MOOCs are on the Move: A Snapshot of the Rapid Growth of MOOCs. *European Foundation for Management Development: White Paper: MOOCs-Massive Open Online Courses*.

Salmon, G., (2000). *E-Moderating – the key to teaching and learning online.* London: Kogan Page

Sandeen, C. (2013). Integrating MOOCs into traditional higher education: The emerging "MOOC 3.0" era. *Change: The magazine of higher learning*, *45*(6), 34-39.

Schaffer, J., Huynh, B., O'Donovan, J., Hollerer, T., Xia, Y., & Lin, S. (2016). An analysis of student behavior in two massive open online courses. Paper presented at the 380-385. Retrieved from http://ezaccess.libraries.psu.edu/login?url=https://search.proquest.com/docview/1844114461?accountid=13158

Schmidt, D. C., & McCormick, Z. (2013, October). Producing and delivering a coursera MOOC on pattern-oriented software architecture for concurrent and networked software. In

Proceedings of the 2013 companion publication for conference on Systems, programming, & applications: software for humanity (pp. 167-176). ACM.

Seaton, D. T., Bergner, Y., Chuang, I., Mitros, P., & Pritchard, D. E. (2014). Who does what in a massive open online course?. *Communications of the ACM*, *57*(4), 58-65.

Shah, D. (2016). Monetization Over Massiveness: Breaking Down MOOCs by the Numbers in 2016. *EdSurge news* Retrieved on December 29th, 2016 https://www.edsurge.com/news/2016-12-29-monetization-over-massiveness-breaking-down-moocs-by-the-numbers-in-2016

Shah, D. (2015). MOOCs in 2015: Breaking down the numbers. *EdSurge news* Retrieved on June 9th, 2016 https://www.edsurge.com/news/2015-12-28-moocs-in-2015-breaking-down-the-numbers

Shen, C., & Kuo, C. (2015). Learning in massive open online courses: Evidence from social media mining. *Computers in Human Behavior, 51*, 568-577. http://dx.doi.org/10.1016/j.chb.2015.02.066

Siemens, G. (2005). Connectivism: A learning theory for the digital age. *International journal of instructional technology and distance learning*, *2*(1), 3-10.

Sims, R. (1999). Interactivity on stage: Strategies for learner-designer communication. *Australasian Journal of Educational Technology*, *15*(3).

Song, Y., Hu, Z., & Gehringer, E. F. (2017). Collusion in educational peer assessment: How much do we need to worry about it? Paper presented at the 1-8. Retrieved from http://ezaccess.libraries.psu.edu/login?url=https://search.proquest.com/docview/1977249121?accountid=13158

Song, Z. X., Cheung, M. F., & Prud’Homme, S. (2017). Theoretical Frameworks and Research Methods in the Study of MOOC/e-Learning Behaviors: A Theoretical and Empirical

Review. In *New Ecology for Education—Communication X Learning* (pp. 47-65). Springer, Singapore.

Swinnerton, B., Hotchkiss, S., & Morris, N. P. (2017). Comments in MOOCs: who is doing the talking and does it help?. *Journal of Computer Assisted Learning*, *33*(1), 51-64.

Swinnerton, B. J., Morris, N. P., Hotchkiss, S., & Pickering, J. D. (2017). The integration of an anatomy massive open online course (MOOC) into a medical anatomy curriculum. *Anatomical sciences education*, *10*(1), 53-67.

Tabachnick, B. G., Fidell, L. S., & Ullman, J. B. (2007). *Using multivariate statistics* (Vol. 5). Boston, MA: Pearson.

Takaffoli, M., & Zaïane, O. R. (2012). Social network analysis and mining to support the assessment of online student participation. *ACM SIGKDD Explorations Newsletter*, *13*(2), 20-29.

Tawfik, A. A., Reeves, T. D., Stich, A. E., Gill, A., Hong, C., McDade, J., ... & Giabbanelli, P. J. (2017). The nature and level of learner–learner interaction in a chemistry massive open online course (MOOC). *Journal of Computing in Higher Education*, *29*(3), 411-431.

Tong, T., & Li, H. (2018). Demand for MOOC-An Application of Big Data. *China Economic Review*, *51*, 194-207.

Tucker, C. S., Dickens, B., & Divinsky, A. (2014, August). Knowledge discovery of student sentiments in MOOCs and their impact on course performance. In *ASME 2014 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference* (pp. V003T04A028-V003T04A028). American Society of Mechanical Engineers.

Uden, L., Sinclair, J., Tao, Y. H., & Liberona, D. (Eds.). (2014). *Learning Technology for Education in Cloud-MOOC and Big Data: Third International Workshop, LTEC 2014, Santiago, Chile, September 2-5, 2014. Proceedings* (Vol. 446). Springer.

University of Edinburgh. (2013). *MOOCs @ Edinburgh 2013 – Report # 1*.

Veletsianos, G., & Shepherdson, P. (2016). *A systematic analysis and synthesis of the empirical MOOC literature published in 2013–2015. The International Review of Research in Open and Distributed Learning, 17(2).*

Vie, J. J., Popineau, F., Bruillard, É., & Bourda, Y. (2018). Automated Test Assembly for Handling Learner Cold-Start in Large-Scale Assessments. International Journal of Artificial Intelligence in Education, 28(4), 616-631.

Wang, Z., Anderson, T., Chen, L., & Barbera, E. (2017). Interaction pattern analysis in cMOOCs based on the connectivist interaction and engagement framework. *British Journal of Educational Technology, 48*(2), 683-699.

Wang, X., Yang, D., Wen, M., Koedinger, K., & Rosé, C. P. (2015). Investigating How Student's Cognitive Behavior in MOOC Discussion Forums Affect Learning Gains. *International Educational Data Mining Society*.

Wang, Y., Yuan, J., & Luo, J. (2015, October). America Tweets China: A fine-grained analysis of the state and individual characteristics regarding attitudes towards China. In *2015 IEEE International Conference on Big Data (Big Data)*(pp. 936-943). IEEE.

Wanstreet, C. E. (2006). Interaction in online learning environments: A review of the literature. *Quarterly Review of Distance Education*, *7*(4), 399.

Wasserman, S., & Faust, K. (1994). *Social network analysis: Methods and applications* (Vol. 8). Cambridge university press.

Watson, S. L., Loizzo, J., Watson, W. R., Mueller, C., Lim, J., & Ertmer, P. A. (2016). Instructional design, facilitation, and perceived learning outcomes: an exploratory case study of a human trafficking MOOC for attitudinal change. *Educational Technology Research and Development*, *64*(6), 1273-1300.

Watson, S. L., Watson, W. R., Yu, J. H., Alamri, H., & Mueller, C. (2017). Learner profiles of attitudinal learning in a MOOC: An explanatory sequential mixed methods study. *Computers & Education*, *114*, 274-285.

Webb, N. M. (1989). Peer interaction and learning in small groups. *International journal of Educational research*, *13*(1), 21-39.

Wei, X., Lin, H., Yang, L., & Yu, Y. (2017). A convolution-LSTM-based deep neural network for cross-domain MOOC forum post classification. *Information*, *8*(3), 92.

Wellman, B., & Berkowitz, S. D. (Eds.). (1988). *Social structures: A network approach* (Vol. 2). CUP Archive.

Wen, M., Yang, D., and Rose, C. (2014, July). Sentiment Analysis in MOOC Discussion Forums: What does it tell us? *Proceedings of the 7th International Conference on Educational Data Mining* (EDM 2014), 130-137.

Williams, J., Li, N., Kim, J., Whitehill, J., Maldonado, S., Pechenizkiy, M., ... & Heffernan, N. (2014). The MOOClet framework: Improving online education through experimentation and personalization of modules.

Wilson, R. E., Gosling, S. D., & Graham, L. T. (2012). A review of Facebook research in the social sciences. *Perspectives on psychological science*, *7*(3), 203-220.

Wise, A. F., Cui, Y., Jin, W., & Vytasek, J. (2017). Mining for gold: Identifying content-related MOOC discussion threads across domains through linguistic modeling. *The Internet and Higher Education*, *32*, 11-28.

Wong, J. S., Pursel, B., Divinsky, A., & Jansen, B. J. (2015, March). An analysis of MOOC discussion forum interactions from the most active users. In *International Conference on Social Computing, Behavioral-Cultural Modeling, and Prediction* (pp. 452-457). Springer, Cham.

Wu, T., Yao, Y., Duan, Y., Fan, X., & Qu, H. (2016). NetworkSeer: Visual analysis for social network in MOOCs. *IEEE Conferences*, , 194-198. http://dx.doi.org/10.1109/PACIFICVIS.2016.7465269

Yang, D., Sinha, T., Adamson, D., & Rosé, C. P. (2013, December). Turn on, tune in, drop out: Anticipating student dropouts in massive open online courses. In *Proceedings of the 2013 NIPS Data-driven education workshop* (Vol. 11, p. 14).

Yuan, L., Powell, S., & Olivier, B. (2014). *Beyond MOOCs: Sustainable online learning in institutions – A white paper.* UK: Cetis – Centre for Educational Technology, Interoperability and Standards. University of Bolton. Retrieved from http:// publications.cetis.org.uk/wp-content/uploads/2014/01/Beyond-MOOCs- Sustainable-Online-Learning-in-Institutions.pdf.

Zhang, J., Skryabin, M., & Song, X. (2016). Understanding the dynamics of MOOC discussion forums with simulation investigation for empirical network analysis (SIENA). *Distance Education*, *37*(3), 270-286.

Zhu, M., Sari, A., & Lee, M. M. (2018). A systematic review of research methods and topics of the empirical MOOC literature (2014–2016). *The Internet and Higher Education*.

Appendix

Pre-survey

Demographic Information from Coursera Platform

- What is your gender?
- In what year were you born (please enter 4 digits)?
- In what country were you born?
- In what country do you currently live?
- Are you of Spanish, Hispanic or Latino origin or descent?
- What is your race? (Select one or more.)

  - American Indian or Alaska Native - East Asian - South Asian - Other Asian

  - Black or African American - Native Hawaiian or Other Pacific Islander

  - White or Caucasian - Decline to state
- What is the highest level of school you have completed or the highest degree you have received?
- Are you currently enrolled as a student in an educational program?
- If you are currently enrolled in an educational program, which of the following best describes the lowest level program in which you are currently enrolled?
- If you have completed an associate, bachelor's, masters, professional school, or doctorate academic degree, please indicate the subject area(s) of your degree(s). (If you have not completed any degree, then leave this question blank.)

  - agriculture and natural resources

  - architecture and related services

  - area, ethnic, cultural, gender, and group studies

  - biological and biomedical sciences

- business, management, marketing
- communication, journalism, and related programs
- communications technologies
- computer and information sciences
- construction trades
- education
- engineering
- engineering technologies and engineering-related fields
- English language and literature/letters
- family and consumer sciences/human sciences
- foreign languages, literatures, and linguistics
- health professions and related programs
- homeland security, law enforcement, and firefighting
- legal professions and studies
- liberal arts and sciences, general studies, and humanities
- library science
- mathematics and statistics
- mechanic and repair technologies/technicians
- military technologies and applied sciences
- multi/interdisciplinary studies
- parks, recreation, leisure, and fitness studies
- personal and culinary services
- philosophy and religious studies
- physical sciences and science technologies
- precision production

- psychology

- public administration and social services

- social sciences and history

- theology and religious vocations

- transportation and materials moving

- visual and performing arts

- other

- Which of the following best describes your current employment status?
- If you are currently employed or seeking employment, which of the following best describes your industry?
- What is your English proficiency in each of the following areas?

- writing - reading - speaking

- Besides English, what other languages do you speak?

- Arabic - Bengali - Chinese (Cantonese) - Chinese (Mandarin)

- Chinese (Wu) - French - German - Hindi - Italian

- Korean - Japanese - Javanese - Malay/Indonesian - Persian

- Portuguese - Punjabi - Russian - Spanish - Telugu - Vietnamese

- Marathi - Tamil - Thai - Turkish - Urdu - Other-text

- Additional comments
- State (US)

VITA

Qiyuan Li

EDUCATION

The Pennsylvania State University, University Park, PA — Aug. 2012 - Present
*Ph.D. in **Learning, Design and Technology*** — *Minor: **Statistics***
Shaanxi Normal University, China — *M.S. in **Psychology*** — Aug. 2009 - May 2012
China Mining & Technology University *B.E. in **Engineering*** — Aug. 2004 - May 2008

RELEVANT PROJECTS

Knowledge Sharing Pattern in An Online Affinity Space for Diabetes Patients
Data Analyst — Nov. 2018 – Present

Institutional Workflow Optimization Supported by Machine Learning Algorithms
Data Analyst Graduate Assistant — Oct. 2018 – Present

Examining the Effects of Learners' Background and Social Network Position on Content-Related Interaction via the MOOC Platform
Principal Investigator — Sep. 2017 – Present

ClassGotcha: Data-Driven Personalized Online Learning Platform
Principal Investigator — Jun. 2016 - Jan. 2018

Penn State Student's Performance and Preference on Different Online Learning Environments
Data Analyst Graduate Assistant — Aug. 2016 - Jul. 2017

Examining Science Learning Using Mobile Devices and Social Media
Research Assistant — Aug. 2014 - Aug. 2016

Designing Online Training Program for the Improvement of Scientific Creativity
Instructional Designer — Aug. 2009 - May 2012

Evaluation of the Effects of the New National Curriculum in Northwest China
Data Analyst and Group Leader — Aug. 2009 - May 2012

TECHNICAL SKILLS

Python, R, SQL, SAS, SPSS, NVivo, Studiocode.

DATA ANALYSIS COURSES

Data Mining I & II	Regression Methods	Applied Time Series Analysis
Analysis of Variance	Categorical Data Analysis	Structural Equation Modeling
Multivariate Data Analysis	SAS Programming	Probability Theory I & II