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Xin Li
University of Melbourne

Karin Verspoor
University of Melbourne

Kathleen Gray
University of Melbourne

Stephen Barnett
University of Wollongong, sbarnett@uow.edu.au

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Analysing Health Professionals' Learning Interactions in an Online Social Network: A Longitudinal Study

Xin LI[a,1], Karin VERSPOOR[a], Kathleen GRAY[a] and Stephen BARNETT[b]
[a] *Health and Biomedical Informatics Research Centre, University of Melbourne*
[c] *General Practice Academic Unit, Graduate School of Medicine, University of Wollongong*

Abstract. This paper summarises a longitudinal analysis of learning interactions occurring over three years among health professionals in an online social network. The study employs the techniques of Social Network Analysis (SNA) and statistical modeling to identify the changes in patterns of interaction over time and test associated structural network effects. SNA results indicate overall low participation in the network, although some participants became active over time and even led discussions. In particular, the analysis has shown that a change of lead contributor results in a change in learning interaction and network structure. The analysis of structural network effects demonstrates that the interaction dynamics slow down over time, indicating that interactions in the network are more stable. The health professionals may be reluctant to share knowledge and collaborate in groups but were interested in building personal learning networks or simply seeking information.

Keywords. Social network analysis, health professional education

Introduction

As medical knowledge expands and healthcare delivery becomes more complex, health professionals must commit to continuous learning to maintain up-to-date knowledge and skills. One approach to meeting their learning and development needs is through engagement in Online Social Networks (OSN) [1]. OSN have been found useful to reduce professional isolation and support anytime-anywhere peer-to-peer interaction at scale. Also, they are thought to contribute to the development of professional networks and improve continuing professional development.

There are many OSN targeted towards health professionals but the interaction occurring in those OSN is generally low, and they appear to fail to support the broader objectives [2]. It has been recognised that there is a lack of understanding about how learning occurs in OSN, making it difficult to design and facilitate this type of learning. To realise the full potential of OSN for health professionals, understanding and evaluating this learning context is important. The first step in such evaluation is to understand the interaction within their learning environment; this in turn helps to

[1] Corresponding Author: Xin Li; E-mail: xinli87@gmail.com.

understand learning behaviours and provides valuable information for educational designers to design effective interventions that optimise the learning environment.

Previous studies have focused mostly on the overall experience or process of learning occurring in an OSN and reflect only a temporary state of the learning network. However, learning is an on-going process. The aim of this paper is to present a longitudinal study of learning interactions occurring over three years among health professionals in an OSN established specifically for registered practitioners, based on data from an online discussion forum that supported this OSN. By combining the techniques of Social Network Analysis (SNA) and statistical modelling, we identified changes in patterns of interaction over time and tested associated structural network effects that could explain these changes as features of the learning process in this OSN.

1. Background and Related Work

Recent technological changes, in particular, social web technologies such as OSN, have reorganised how people learn and given rise to the concept of networked learning. Goodyear [3] defines networked learning as the learning in which information and communications technology are used to promote connections between learners, and between a learning network and its learning resources. The study of networked learning aims to understand the learning process by investigating how people develop and maintain a web of social relations for learning; it focuses on the diversity of social relationships (rather than the development of long-lasting relationships), and the value such diversity creates for learning.

SNA is a technique that allows analysis of human interaction and relationships between individuals. It offers a way to proceed from these theories to undertake studies of learning interaction in an OSN. The application of SNA to learning is still at a very early stage [4]. Basic SNA measures such as centrality have been used to study the patterns of interactions occurring among teachers in their OSN [5], and to understand the flow of experiential knowledge sharing among health professionals within a paediatric pain discussion forum [6]. However, these studies were limited in their cross-sectional analysis and based on small numbers. A recent review of SNA-based studies of learning [7] has found that although statistical models contribute to the longitudinal analysis of a learning network, the majority of studies have yet to employ statistical models to explain changes of network structure and learning behaviours.

2. Methods

2.1. Data

Data were collected from the database of an online discussion forum provided by the health professional OSN host organisation, with Human Research Ethics approval. Discussion forum data from the period 2012 to 2014 were selected and grouped into three datasets of one-year duration. Within these datasets, data were extracted on the activities of 48 forum participants who were present in all three years. The three-year period represents 50% of the overall operating period of this forum, and the most recent and complete years available at the time of data collection in 2015. The 48 forum participants represent 13% of overall participants during this period. Trial and error using SNA on the forum database showed that one-year-long datasets were the minimum duration required to evolve significant connections among these participants.

2.2. Measures

To investigate the learning interaction and structural changes over time, SNA network-level measures (i.e. density, centralisation, diameter and average path length, as defined in Table 1) were used to reveal the participation level and connectivity among participants. In addition, the patterns of interactions were visualised to enrich the findings of the network measures.

Table 1. Descriptive definitions of SNA measures

SNA measure	Descriptive definition
Density	The number of present connections as a ratio of the possible number of connections.
Centralisation	The extent to which the connectedness is focused around a particular user.
Diameter	The longest step between any pair of users in a network.
Average path length	The average step between any pair of users in a network.

To identify the structural properties of interactions and test the significance of their effects in the network, Stochastic Actor-Oriented Models (SAOM) [8] was employed. This approach considers the totality of all possible network configurations of a given set of actors (health professionals, in this case) as the state space of a stochastic process, and models the observed network dynamics by specifying parametric models for the transition probabilities between these states.

In this study, SAOM was used to examine which micro structures might play a statistically significant role in the process of learning. In addition, it was used to determine whether health professionals' characteristics (i.e. gender and geographic location) might affect changes in the patterns and structure of learning interaction.

The network effects considered in this study were transitivity and homophily. Transitivity reflects the extent to which participants who interacted with one person in common also interacted with each other (i.e. if A is linked to B and B is linked to C, then C is also linked to A). Homophily indicates the extent to which participants interacted with others with similar attributes (e.g. gender and geographic location).

2.3. Procedure

Network construction: Participants were connected in the online discussion forum through their participation on individual threads. Each participant is a node in the network, labelled by an identity number. We considered that a connection was created between two participants if they both contributed to the same thread. A network was formed by taking all of these participants together with their connections. Since the network was used for learning, we called it a Learning Network (LN). We formed three LNs by extracting their participation in each year (i.e. 2012, 2013, and 2014). We noted gender and geographical location attributes for each participant.

Social Network Analysis: SNA network-level measures were calculated separately for each of the three LNs. The `statnet` library in `R` was used for the calculation and analysis. The `igraph` library was used to provide visualisation.

Statistical Modelling: Statistical modelling was performed using the `SIENA` library in `R` (`RSiena`). The learning interaction of 48 participants in the three LNs was given the role of the dependent variable. Their gender and geographic location attributes were defined as explanatory (independent) variables. The `siena07` function was used for estimation of the parameters by fitting the specified model to our dataset.

3. Results and Discussion

3.1. Network-Level Measures

Table 2 presents the network-level measures for the three LNs. The overall low density scores (<0.5) indicate a low level of participation among these participants. The decline in the density score indicates a decreasing level of participation over time. The low centralisation score of LN1 and LN3 (<0.5) indicates the network was not centralised continuously over the three years of networked learning that we examined. The centralisation of LN2 (0.68) demonstrates that the interaction in the middle year was centralised, while most were not engaged and interacted infrequently. It is unknown from this result why centralisation was happening only in the middle year. The overall high diameter result (>2) shows that in general participants were not very close to each other in terms of interaction steps, but the low average path length confirms that most of them were as close to each other as one or two interaction steps. This therefore indicates that there were only a few participants who were distant from the core group and thus might not easily share knowledge.

Table 2. Network-level measures of LN1, LN2, and LN3

Network measure	LN1	LN2	LN3
Density	0.31	0.27	0.17
Centralisation	0.43	0.68	0.49
Diameter	3	4	5
Average path length	1.77	1.78	2.13

3.2. Network Visualisation

Figure 1 presents the visualisation of the three LNs. To reveal the patterns of interaction, we optimised the layout by applying a layout algorithm that directs the most highly connected nodes into the centre of the graph. We thinned all networks by displaying only those ties that pass a minimum threshold (specifically, we kept only those ties that had a weight greater than the mean weight plus one standard deviation).

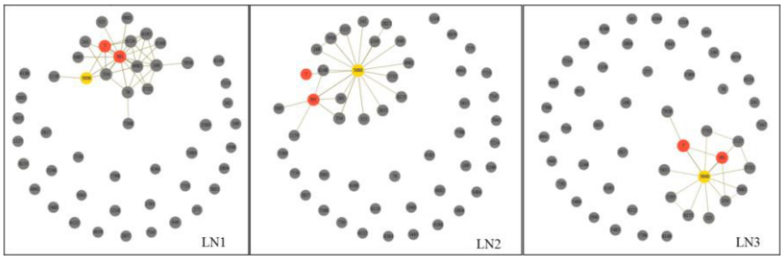

Figure 1. Interaction patterns of LN1, LN2, and LN3

In LN1, we observe that approximately 40% of participants (N=18) sat in the centre of the network; they were engaged and actively participating. Analysis of OSN member identification data showed that this included two moderators (orange dot) who had a formal facilitation role in the discussion forum. Unsurprisingly these two contributed the most to the discussion threads.

In LN2, we see less participation overall as compared to LN1. There was one member (yellow dot) informally leading the network – this core member interacted directly and frequently with a number of other users, but little conversation occurred directly between those other users. The moderators moved more towards the side and one moderator became a "broker" who helped to bridge the discussion among users as indicated by one of the orange dots.

In LN3, we see that more participants moved to the edge of the network. More conversation started happening among the participants in the central, led by the same core member who led LN2.

The user identity numbers shown in the three LNs indicate that the majority of active participants (other than the moderators and the core member) did not remain in the centre and stay engaged over time.

Furthermore, a visualisation of interactions provides some insights on why the network was centralised only in LN2 – because when the core member took over the effective lead role from the moderators, the discussion was occurring between him and other participants. As shown, the participants only started interacting with each other, independently of the core member, again in the following year. This reflects a tendency for the network to become temporarily centralised if there is a change in the lead role.

3.3. SIENA Models

The `RSiena` program was used to test the significance of structural effects of the network. The results of the effects on structural parameters are summarised in Table 3. The significance of each effect can be tested using t-value, which is defined by dividing the parameter estimate by its standard error. It measures how many standard errors the estimate is away from zero. Generally, any t-value greater than +2 or less than -2 is acceptable.

Table 3. Estimation results for structural parameters

Parameter	Estimate	Standard error	T-value
Rate period 1	27.16	5.93	4.58
Rate period 2	19.03	2.58	7.38
Degree	-2.67	0.11	-23.85
Transitive triads	0.25	0.14	1.84
Distance-2	0.13	0.03	4.43
Same gender	0.03	0.06	0.54
Same geographic location	0.11	0.07	1.48

The rate parameter indicates a frequency at which network changes are estimated to occur. The changes of network structure are affected when a participant starts or stops interacting with other participants. Since we have two consecutive observations within the three-year period, Rate period 1 and Rate period 2 indicate the first and second observation, respectively. As shown, the considerable greater value of Rate period 1 (27.16) in relation to the value of Rate period 2 (19.03) suggests the interaction dynamics slowdown from the first to the second observation year, indicating a stabilised interaction in the network. The Degree parameter estimates the change in the number of connections for a participant between two periods, so its negative effect, in this case, confirms the stabilising tendency within the network.

Both Transitive triads and Distance-2 parameters are indicators of transitivity. Transitive triads estimate the number of transitive patterns (i.e. if participant A interacts with participant B and participant B interacts with participant C, then participant A interacts with participant C). The Distance-2 parameter estimates the number of shortest path lengths equal to 2, and it expresses transitivity inversely.

As shown, the estimation result of the Transitive triads effect is not statistically significant so we do not consider it further. However, the estimation of Distance-2 parameter indicates a positive (0.13) and statistically significant value, so we conclude that network did not reveal any transitivity effect, and therefore suggests that there were numerous null connections and little groups formed in the network, indicating a relatively sparse network in which information (or learning resources) will have difficulty flowing from one part of the network to another. This may suggest that there was little knowledge shared among groups – the health professionals did not form collaborative groups. Instead, they interacted with one or more selected individuals to build personal learning networks, or simply to seek information in the network. This relates to an earlier work in understanding how health professionals behave online [9], which suggested that health professionals were highly strategic online in seeking information to solve problems and build careers.

Both parameters of the Same gender and Same geographical location are homophily effects considered in this network, they indicate the preference for health professionals of the same gender or geographic location. Although the concept of homophily associates certain network structures with the similar actor attributes within a network [8], the estimation results for both parameters of homophily in this study indicate a positive but not statistically significant homophily effect, which means there is no pattern of learning common to either characteristic.

One limitation of this study is that considering the overall activity in the discussion forum within this OSN, data were analysed very selectively. Other means of interaction among OSN members (e.g. twitter, live chat) could be added to the dataset to enrich the findings. In addition, due to limitations of the data source, passive users (i.e. those who learn by reading but do not participate in any discussion) were not tracked in our study.

4. Conclusions and Future Work

OSN has potential as an innovative approach to the professional development of health professionals. However, we need to gain a clear understanding of how the process of online interaction can be considered to be educational so that this learning process can be effectively evaluated. This paper has shown how, by combining the techniques of SNA and statistical modelling, it is possible to identify changes in patterns of interaction and test associated structural network effects in a social learning network.

From our analysis, we conclude that the participation level in the network was low in general. The participants did not stay engaged for a long period of time; many were shown to be distant from the core group and did not participate in sharing knowledge. Over time, a small set of participants remained active; some even began to lead discussions, as can be seen in the change of network structure. This finding is consistent with other research that has found evidence of a small set of users producing the bulk of the discussion within online communities. In addition, the analysis has shown that a change of lead role results in a change in the network structure and learning interaction occurring in the network.

By applying the statistical model SAOM, we tested structural network effects (homophily and transitivity) and demonstrated that this network stabilised over time. The homophily effect was not statistically significant, indicating that there was no pattern of learning common to gender or geographic location. The lack of transitivity effect suggests a sparse network, indicating the health professionals in this study were reluctant to share knowledge and collaborate in groups, they may be interested in building personal learning networks or simply seeking information. This may explain why, in other studies, the interaction in health professional networks is low and appears to fade quickly. In theory, establishing transitivity is important for a learning network, as it helps form exclusive learning groups over time so that learners can build learning relationships, construct knowledge and learning from each other [10]. However, this might not be the case when designing a social learning network for health professionals – our analysis suggests that, instead of encouraging them to form collaborative learning groups, we should support health professionals to assess connections and target interactions that will help them to exploit learning opportunities whose meaning and value are more readily recognised and rewarded.

Further research is under way to investigate the contents of discussion in this OSN to provide an integrated explanation of how the knowledge of these health professionals was constructed in the network. In addition, since the specific user-level context for interaction (e.g. the participant's learning goals and background) was not captured and they may influence interaction behaviours and network pattern changes, we plan to work with the participants to understand their learning context to enhance the interpretation of interaction results.

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