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ORIGINAL RESEARCH

Social Network Analysis: A Framework for Identifying Communities in Higher Education Online Learning

Shazia K. Jan[1] · Panos Vlachopoulos[2]

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Abstract

This paper presents the Integrated Methodological Framework (IMF) which uses social network analysis (SNA) to structurally identify communities in higher education online learning (HEOL). Decades of research speaks for the value of community-based learning albeit in traditional, blended, or online environments. The communities of practice (CoP) and community of inquiry (CoI) are well-established, empirically tested frameworks that have been effectively used for exploration of community-based learning in professional and educational contexts. Typically, research using these frameworks has required extensive qualitative analysis making it tedious and time-consuming. Pivoting on structural similarities between networks and communities, the IMF embeds SNA constructs in structural components of the CoP and CoI frameworks. By structurally identifying a CoP and CoI, the IMF allows targeted, selective qualitative analysis thus reducing the extent of qualitative analysis required previously in research using the CoP and CoI frameworks. Application of the IMF is demonstrated in a case study on an online blogging network. The study substantiates the IMF as an effective framework for structural identification of a CoP and CoI. The validity and robustness of the IMF is being further tested in ongoing research.

Keywords Social network analysis · Learning analytics · Online learning · Communities of practice · Community of inquiry · Methodological framework

✉ Shazia K. Jan
shazia.k-jan@hdr.mq.edu.au

Panos Vlachopoulos
panos.vlachopoulos@mq.ed.au

[1] Macquarie University, C3A, First Walk, Central Campus, Rm. 923, Sydney, NSW 2109, Australia

[2] Macquarie University, Y3A-10, Hadenfield Avenue, Rm. 239, Sydney, NSW 2109, Australia

1 Introduction

Online learning[1] is growing at an exponential rate (Seaman et al. 2018) and is becoming increasingly sophisticated with continuing advancements in technology. Numerous learning design frameworks and models have emerged over the past couple of decades some of which are widely applied for designing complex online learning environments. However, despite the hype and interest in the field, there is limited research on the pedagogical impact of learning designs (Bower 2017). Learning analytics, defined as the "measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs" (LAK 2011, para. 6), has relatively recently gained the attention of educational researchers due to accessibility to extensive data stored in learning management systems (LMS). Most commonly log data from LMSs is used to predict such things as student performance and retention (Lockyer et al. 2013). Social learning analytics which comprises of techniques for investigating social learning processes (Shum and Ferguson 2012) is increasingly being used by educational researchers as well.

Social network analysis (SNA), a sub-category of social learning analytics, is a multidisciplinary technique consisting of quantitative analytical methods based on unique theoretical constructs. It is conducted on networks of relationships between human and/or non-human entities (e.g. technology, documents and, organizations, etc.). The entities in a network are represented by nodes and the relationships by lines between the nodes. Networks can be one-mode (one type of entity) or two-mode (two different types of entities). Relationships within a network can be one or multiple and of any type (e.g. friendship, colleagues, or kinship). Networks can be directed (lines connecting the nodes are arrows), identifying the initiator and receiver of a relationship, and/or weighted (thickness of line or arrow indicates strength of the relationship). SNAs' methodological distinctness lies in its emphasis on relational as opposed to attributional properties of data and the intuitive visual representations it affords (Wasserman and Faust 1994). SNA comprises of numerous constructs which can applied at the whole network, sub-group and, individual levels. SNA has been used, among other things, for the investigation of pedagogical dynamics of group structures and communities in e-learning (Cela et al. 2015), however, the lack of appropriate pedagogical grounding has made findings vulnerable to interpretations (De Laat and Prinsen 2014; Shea et al. 2013).

Networks form in any learning environment albeit face-to-face, blended or purely online as individuals and resources interact in the virtual and/or physical space. In this paper, our analysis and discussion is restricted to one-mode networks comprising of individuals and their interactions within a LMS only. Connections in a network in and of themselves do not signify learning but represent the potential to learn by laying out channels through which information and resources can travel to create knowledge. A network does however form the foundation of the pedagogically significant construct of a *community* of learning. All communities are networks, however not all networks are communities and the educational affordances of the two differ (Wenger et al. 2011). A network is defined as, "a set of connections among people… used for solving problems, sharing knowledge, and making more connections" (Wenger et al. 2011, p. 9). Alternatively, a community is, "a group of

[1] The terms "online learning" and "e-learning" include purely online and blended courses and have been used inter-changeably where necessary.

individuals identifiable by who they are in terms of how they relate to each other, their common activities and ways of thinking, and their beliefs and values" (Biza et al. 2014, p. 162). The importance of learning in a community is a widely-held belief resting on decades of research (Zhao and Kuh 2004). Communities are considered as essential for knowledge generation which is an integral component of the learning process (Garrison and Anderson 2003). Learning in various forms of community has been described as "necessary for creating and confirming meaning and…essential for achieving effective critical thinking" (Swan et al. 2009, p. 4).

In a learning environment, the formation of networks is inevitable. The pedagogical effectiveness of community-based learning and structural parallels between networks and communities make SNA the natural choice of methodology for exploring communities of learning in the online space. In this methodological paper, we present a theoretically informed Integrated Methodological Framework (IMF) for structurally identifying communities of learning in higher education online learning (HEOL). The IMF grounds SNA in structural components of empirically tested and well-established community-based learning frameworks, namely, the communities of practice (CoP) (Lave and Wenger 1991) and community of inquiry (CoI) (Garrison et al. 2000). The IMF includes macro and micro level SNA constructs corresponding to overall network structure and individual nodes. We begin by presenting the rationale for development of the IMF followed by a synopsis of the structural components of the CoP and CoI frameworks. We then present and describe the IMF in detail. Finally, we demonstrate use of the IMF in a case study on an online blogging network.

2 Rationale for Development of the IMF

Motivated by the lack of quantitative research using the CoP and CoI frameworks commonly applied to research in online learning (Shea and Bidjerano 2010; Smith et al. 2017), an interest in SNA, and the relationship between networks and communities, we recently conducted a systematic literature review of research studies that integrate SNA with the CoP and CoI frameworks (Jan et al. in press). The handful of studies (9 using the CoI and 1 using the CoP framework) that met the inclusion criteria were reviewed to specifically: identify the SNA constructs used; examine complementary analytical techniques employed with SNA; assess the effectiveness of SNA as technique for structurally exploring a CoP and CoI and; synthesize limitations of existing research. The dearth of studies found, disparate outcomes of existing studies and, use of limited SNA constructs pointed to the infancy of research in the area especially, the untapped potential of SNA to effectively explore macro and micro level dynamics of learning communities. For instance, results of studies using SNA and the CoI framework varied depending on the context of the study, e.g. in a study (Shea and Bidjerano 2010) on a discussion forum, no relationship was found between centrality (see Sect. 4.4.3) and cognitive presence (CP) (see Sect. 3.2), whereas another study (Jimoyiannis et al. 2012) on a blogging network reported a positive association between centrality and CP. The review did however validate the capacity of SNA to identify key groups and participants within large networks, the qualitative analysis of whose interactions would be indicative of dominant components of a CoP and CoI thereby greatly reducing the need for extensive qualitative analysis of all interactional data. Most importantly, the review hi-lighted key gaps in existing research, that is: to date no research has considered how SNA can be used to identify a CoP or a CoI based on the overall structural characteristics of a network; there has been no examination of the relationship between learning and participation in a community, assuming performance in a course of study indicates learning; there has been no investigation on the impact of community structure on the nature and quality of interactions and; a narrow range of SNA constructs have been used repeatedly prompting the notion that there might be other constructs that correspond more appropriately with certain components of a CoP and CoI. These critical conclusions from the review guided us and acted as key drivers for development of the IMF. Before presenting the IMF, we outline its' theoretical underpinnings which comprise of certain components of a CoP and CoI. The aim here is to establish the structural link between SNA and the CoP and CoI frameworks.

3 Theoretical Underpinnings of the IMF

Dating as far back as early 1900s, the concept of learning communities has undergone significant evolution (Fink and Inkelas 2015). The flexibility to communicate and collaborate irrespective of time and space provided by technology has redefined community-based learning leading to the emergence of various models of learning comprising of different types of communities, for instance, learning communities, knowledge-based communities and, personal learning networks. The CoP and CoI are two popular, well-tested, community-based pedagogical frameworks that have been commonly applied to online learning (Conole et al. 2011). While both frameworks are driven by the social dimension of learning, learning and teaching dynamics within each are unique, leading to different structural representations of the underlying networks which therefore allows for distinct interpretation of SNA constructs.

3.1 Communities of Practice

Despite successive revisions since the introduction of the theory of situated learning (Lave and Wenger 1991), the essence of the CoP framework remains the same to date. A CoP represents a group of individuals whose shared interests bring them together in a network of relationships to form a practice characterized by mutual engagement and a shared repertoire of resources (Wenger et al. 2002). Mutual engagement refers to interactions between individuals which occur within a network and lead to rhythms of participation and non-participation (Wenger et al. 2009). The process of legitimate peripheral participation or identity development (Lave and Wenger 1991) signifies learning as newcomers evolve into experts and progressively move from the periphery to the centre of the community. These progressions or learning trajectories are classified as: full participation (insider); legitimate peripherality (inbound trajectory to becoming a full participant or in a circular trajectory around the periphery); marginality (outbound trajectory and is either moving from being a full participant to becoming an outsider or is restricted to the periphery) and; full non-participation (outsider) (Wenger 1998). Structural changes in a network over time would depict these learning trajectories which signify legitimate peripheral participation, identity formation and, learning—the critical components of a CoP. The CoP framework is rooted in the notion of professional learning, specifically, the apprenticeship model, and has been applied in the professional learning and knowledge management context extensively (Cross et al. 2006). The framework extends to the educational context and is being increasingly applied as such.

3.2 Community of Inquiry

Grounded in Dewey's (1859–1932) ideas on critical thinking, collaborative learning and, practical inquiry, the CoI framework was specifically developed as a guide for online pedagogical practices and research (Garrison 2017). It is one of the most widely cited and used frameworks and has empirically proven to be effective in explaining individual and collective learning in traditional and e-learning contexts (Shea and Bidjerano 2010). The CoI framework is a learning centred, process model driven by the intricate dynamics between different stages of three intersecting presences: social presence (SP); teaching presence (TP) and; cognitive presence (CP). Garrison et al. (2000) define SP as "the ability of participants in a community of inquiry to project themselves socially and emotionally as 'real' people…" (p. 94) and CP as "the extent to which learners are able to construct and confirm meaning through sustained reflection and discourse" (p. 89). TP is described as a presence that "manages the environment and focuses and facilitates learning experiences" (Garrison and Kanuka 2004, p. 98). Ample research has been conducted on each of the presences independently however, the dynamic inter-relationships between SP, TP and, CP over a course of study have not been the subject of much investigation (Garrison 2017). Group cohesion or degree of interactions between participants is a component of SP which is always present in a CoI (Garrison 2017). Therefore, it can be reasonably assumed that the overall density of a network signifies the level of SP in a CoI. This assumption has also been validated by recent studies (Shea and Bidjerano 2010; Tirado et al. 2015). SP is an integral precursor to collaboration and critical discourse (CP) and supports and sustains the community once it has been established with a common purpose and academic identity, a function of TP (Garrison 2017). As such, SP can be viewed as the foundation of a CoI supporting CP, also described as the interplay between the public (social and communal) and private (individual) worlds and TP, referred to as an act of doing, embodied by lecturers, tutors, and students alike (Garrison 2017). As a course of study develops, high levels of SP are replaced by TP and CP as participants assume different roles and responsibilities. SP acts as a mediator between CP and TP which becomes more distributed as SP and CP develop (Garrison 2017). As a starting point, taking the degree of interactions as representative of SP, knowledge of the learning design coupled with selective qualitative analysis, would make it possible to ascertain structural dynamics between SP, TP and CP and their respective influence on learning based on properties of the overall network and individual nodes.

4 The Integrated Methodological Framework (IMF)

Having explained the theoretical grounding for the framework, we now present the Integrated Methodological Framework (IMF) for identifying a CoP and a CoI in HEOL based on the structural characteristics of underlying networks. The IMF comprises of a visual illustration of the key concepts underlying the framework as well as four sequential components. It is important to note that Fig. 1 as a stand-alone does not provide sufficient

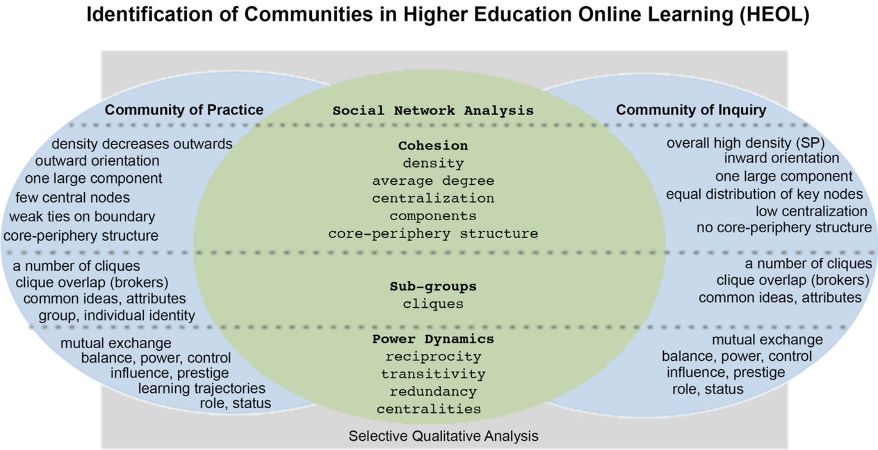


Fig. 1 Integrated Methodological Framework

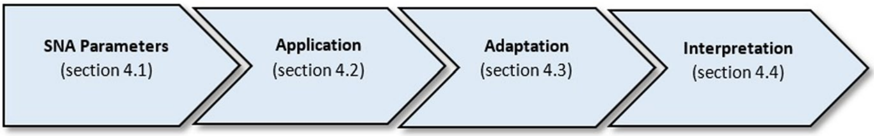


Fig. 2 Components of the Integrated Methodological Framework

information for using the IMF however, we believe the visual is necessary for a conceptual understanding of the framework.

Figure 1 captures the essence of the IMF. That is, being the key methodology driving the framework, SNA is placed in front with corresponding structural components or identifiers of a CoP and CoI positioned behind the SNA constructs on the left and right side respectively. The identifiers in the CoP and CoI columns indicate the SNA constructs expected in each community (explained in detail in Sect. 4.4). The dotted lines in Fig. 1 represent the three different levels of analyses allowed by the IMF, i.e. whole-network, subgroup, and individual level. Selective qualitative analysis is positioned in the background to depict the support it provides to the SNA, if required.

Figure 2 shows the four sequential components of the IMF. Each component precedes the other in the application and interpretation of the framework and is described in detail in the sections indicated in the figure.

4.1 SNA Parameters

SNA is applicable in any context involving relational data however, before using the technique it is necessary to establish certain SNA parameters specific to the context of investigation and address some commonly known challenges with using SNA within the specific context. In the IMF:

- The networks are one-mode in which the nodes represent lecturers, tutors and/or students in a course of study.

Table 1 Matrix of interactions between 5 nodes

	A	B	C	D	E
A	0	3	0	2	0
B	2	0	0	1	0
C	0	1	0	0	1
D	0	0	1	0	1
E	1	0	3	0	0

- The relationships between the nodes comprise of online, text-based interactions, i.e. each interaction is considered as one connection or tie.
- The size of the network is determined by the number of nodes, i.e. students, lecturers, and tutors.
- The network is closed, structured and, restricted to the interactions within the LMS during an activity, therefore, the boundaries of the network are well defined (Laumann et al. 1983).
- Data from the LMS used to create the networks is factual, real-time, and reliable therefore the networks represent valid relationships (Wasserman and Faust 1994).
- The issue of incomplete or missing data (Borgatti and Molina 2003) only arises in two situations: in the case of a longitudinal study in which some students withdraw or join a course later (Grunspan et al. 2014) or in the case of non-consent of participants represented by nodes. These situations become problematic if the missing node is a bridge (connector) between two sub-groups etc. (Borgatti and Molina 2003). Conclusions drawn from networks with missing data need to acknowledge this issue.
- An ethical conflict between subject protection and data set completion (Grunspan et al. 2014) exists as non-participants who have ties with participants are included in the network diagrams. Therefore, in the absence of consent, an in-depth analysis of data associated with non-participants cannot be undertaken—a limitation of SNA.
- LMS data allows for obtaining snap-shots of a network at different points during a learning activity therefore, by comparing successive snap-shots (or time slices) of the network, dynamic social relationships can be examined (Emirbayer 1997).

For further information on SNA we refer interested readers to Borgatti et al. (2013).

4.2 Stages of Application

Networks and communities are dynamic structures continuously evolving with changing levels of engagement of participants. A network forms as soon as two individuals interact however, a community takes time to form (Wenger 1998). Therefore, identification of a community requires static and temporal exploration of the underlying network as it gradually evolves into a CoP or CoI, if at all. Correspondingly, application of the IMF is a multi-stage process whereby each stage determines the actions to be taken in the next. Before going further, it is important to clarify some key terms used henceforth. A *static* network represents a snap-shot of all interactions between nodes in a network at a certain point in time. We refer to a static network as the *cross-section* of a network or the *cross-sectional network* (the terms are used inter-changeably). For instance, in a discussion forum spanning 10 weeks, interactional data extracted at the end of week 1 would be the cross-section of the network at the end of week 1. A *temporal* analysis involves comparing the structural changes (caused by changing relationships or interactions) in successive cross-sections of a network. Hence, the cross-sections represent time-slices of the network. We now describe each stage of application of the IMF in detail.

- *Stage 1—Preparation of data*: Firstly, extract cross-sectional interactional data from the LMS and code into matrices for conducting SNA in software like UCINET (Borgatti et al. 2002). The time at which a cross-sectional network is extracted will vary with the context of investigation. For instance, the design of a learning activity could be such that we need to examine a cross-sectional network after 5 weeks of activity (the cross-section would comprise of cumulative interactions over 5-weeks) as opposed to after 1 week. To create matrices, place participants in rows and columns as shown in Table 1. A value of >0 between two participants indicates a connection or tie and a value of 0 indicates otherwise. The matrix should be weighted indicating the strength of the relationship, that is, the number of times two participants interact (e.g. nodes A and B interact 5 times in total as shown in Table 1), and directed, that is, the initiator and receiver of the interaction is identified (e.g. A initiates interaction with B two of the five times).

Secondly, generate radial network diagrams based on degree-centralities of nodes and weight of edges in software such as Social Network Visualizer (Socnetv 2017). The matrices created in UCINET can be easily imported into Socnetv. The radial diagrams place a participant with the highest number of connections and least distance from others towards the centre of the network. Thirdly, corresponding with the network diagrams, calculate relevant SNA constructs in UCINET. At a minimum, the number of ties, average degree or density, centralization index, number of components, number of nodes in largest component, number of cliques, core nodes, reciprocity and, transitivity should be calculated. Other constructs can be added depending on the research objective and level of analyses required. The SNA constructs and network diagrams can be examined in either order or simultaneously.

- *Stage 2—Static and temporal analysis:* Examine and interpret the SNA constructs and/or diagrams obtained in stage 1 and arrive at a preliminary conclusion regarding the type of community formed, if any (static analysis). Then, guided by the preliminary conclusion, conduct a temporal analysis by comparing successive cross-sectional networks for structural changes, for instance, a changing core-periphery structure, changes in the number of cliques, etc. Such a comparison is necessary to validate preliminary conclusions made from the static analysis. For instance, if a CoP is suspected, a changing core-periphery structure of successive cross-sections signifies the process of legitimate peripheral participation without which we cannot claim the presence of CoP. Changes in reciprocity, transitivity, and sub-group structures in successive cross-sections are indicative of shifting dynamics, roles and statuses, individual and whole-network trajectories, etc. (explained in Sect. 4.4). As another example, if a CoI is observed in a couple of successive cross-sections but does not sustain in the following cross-section, we cannot claim that the learning activity leads to the formation of a CoI. For that we need to look at the overall aggregate (cumulative) network which takes us to the next stage.
- *Stage 3—Aggregate analysis:* Examine cumulative interactions over the entire duration of a learning activity. This examination would include an aggregated network diagram

and the SNA constructs listed in stage 2. Although the aggregated network does not reveal temporal community dynamics, the overall structure of the network indicates the type of community formed over the entire course of an activity.

- *Stage 4—Qualitative analysis:* Having identified the type of community formed, should there be a requirement to conduct qualitative analysis, content of interactional data from key participants (identified by their positions in the network diagrams) can be extracted from the LMS. For instance, in a CoP, if a researcher wants to identify the type of posts that attract others he/she would look at posts of core participants to identify patterns. In a CoI, assuming density represents SP which underlies TP and SP, qualitative analyses could be conducted on dense pockets to assess the presence of CP and TP. Here it is important to note that the IMF identifies a CoP and CoI based on structural characteristics of the frameworks only. Once the type of community has been identified, further detailed analyses including qualitative analysis would be required to confirm the presence of a CoP and/or CoI based on other components of the frameworks. What the IMF does is allow the preliminary identification of the community and reduces the amount of analysis required as selective qualitative analysis can be conducted.

4.3 Adaptation to Context

One important aspect in technology-mediated communities of learning is the role of technology (tools) used to facilitate the process (Wenger et al. 2009). Apart from social media (facebook, twitter, etc.), there are three dominant tools within a LMS that are used for learning purposes: discussion forums; blogs and; wikis. While each of these tools involves asynchronous interactions, each is used for a different purpose which governs the nature of interactions that occur within each. Therefore, we would expect to see different configurations of the relational networks derived from each tool. Thus, the networks derived from discussion forums, blog and wikis are not comparable to one another. Therefore, the IMF needs to be adapted and interpreted considering the affordances of the tool used to foster the creation of communities of learning. Table 2 shows the key differences between discussion forums, blogs and, wikis along with the nature of interactions expected within each tool and an example interpretation for each.

4.4 Interpretation

Certain SNA constructs have been selected for inclusion in the IMF based on their correspondence with parallel structural components of a CoP and CoI and findings from our literature review (Jan et al. in press) discussed in Sect. 2. The SNA constructs have been grouped at the whole-network (cohesion), sub-group (cliques), and individual level (power dynamics). Preliminary identification of a CoP and CoI hinges on measures of network cohesion only. Clique analysis and power dynamics are applied subsequently and interpreted according to the community identified by the measures of cohesion. The following sections describe the SNA constructs and explain interpretations in terms of corresponding a CoP and CoI components.

4.4.1 Cohesion

Measures of network cohesion are used for preliminary identification of a CoP and CoI. The *density* of a network is the total number of ties divided by the total number of

Table 2 Adaptation of the IMF to context

Tool	Discussion forums	Blogs	Wikis
Key features (University of Adelaide 2017)	Topic centred Can be started by anyone on topic of choice Equality of all participants Responses are required for discussion to occur Interested users can follow any topic of interest	Author centred Posts made by the author only Author has dominant presence Comments made on original post Presented in reverse chronological order	Content centred Posts made by a group Development of final post is documented showing individual participation Collaborative activity aimed at reaching consensus Focused on content developed rather than individual participants Comments not included in the content
Nature of interactions	High degree of interactions Chains of nested comments High level of exchange (reciprocity)	Lower degree of interactions Comments not deeply nested Lower level of exchange (reciprocity)	Edits to content represent interactions rather than comments Interactions limited within group Exchange limited to comments within group
Example of interpretation	A student with a number of incoming ties could be involved in an in-depth exchange with a selected few others on a specific topic. Therefore, the student might be a prestigious participant within that particular thread only and not necessarily in the overall discussion forum	A student with a number of incoming ties clearly attracts others to engage with the students' post and therefore holds a prestigious position. If the same student has a number of outgoing ties as well, the student is actively reading and commenting on other posts is therefore influential	A student with high connectivity is a key contributor to the content and holds an influential position

Table 3 Identifiers of a CoP and CoI based on network cohesion

SNA construct	CoP	CoI
Density/average degree	Density of the network decreases from the centre outwards. A few nodes with strong ties (insiders) positioned towards the centre of the network with a number of nodes with weak ties on inbound or outbound trajectories on the periphery. A few isolates (outsiders) that never join the community	Overall dense network indicative of SP with relatively equal distribution of ties and key nodes across the network
Components	One large component	One large component
Network centralization	High network centralization	Low network centralization
Core-periphery structure	A clear core-periphery structure representing legitimate peripheral participation	No core-periphery structure representing equal participation

possible ties. Densities are almost always lower in smaller networks therefore, for comparability, the preference is to use the average degree. The *average degree* is the average number of connections each node has in the network. *Centralization* refers to the degree to which a network is focused on one or a few nodes. The higher the density or average degree and centralization, the greater the cohesion. A highly centralized network is controlled by a few powerful nodes and is therefore restrictive (Carolan 2014). A *component* is a group of nodes in which at least one path connects all nodes. The bigger the main component, the higher the overall cohesion. The *core-periphery structure* of a network identifies nodes that belong to the core and periphery of a network thereby indicating central, influential nodes (Borgatti et al. 2013). Table 3 shows identifiers of a CoP and CoI based on measures of network cohesion.

4.4.2 Sub-groups

Once a community has been identified as a CoP or CoI based on measures of cohesion, sub-group analysis is used accordingly for further investigation. *Cliques* are groups of nodes in which every node is connected to every other node. Cliques represent solidarity, shared norms, trust, identity and, collective behaviour. A comparison of attributes and behaviours of nodes belonging to a clique with nodes in other cliques can provide useful implications for learning depending on the context of analysis (Carolan 2014). Overlapping cliques occur if a node belongs to more than one clique. While we would expect multiple, over lapping cliques in both communities, implications of clique membership differ in a CoP and CoI. Once dominant cliques and nodes in them have been identified, qualitative analysis would be required to isolate components of a CoP and CoI as illustrated by the examples in Table 4.

4.4.3 Power Dynamics

We view power dynamics in terms of the stability of and control within a network. To assess power dynamics we use measures of reciprocity, transitivity, redundancy, and degree centrality (Table 5). The *reciprocity* of a network is the extent to which ties are bi-directional or symmetrical between nodes and shows the direction of information flow. It indicates the network's stability as reciprocated ties tend to be more stable over time. *Redundancy* is the existence of alternate paths between nodes. A t*ransitive* triad occurs when A → B, B → C and A → C. A network with high transitivity appears clumpy with long distances. The higher the transitivity and redundancy of a network, the lower the power and control (Borgatti et al. 2013). Note that the CoP framework does not discuss issues of power and control that are critical determinants of flow of information and resources (Jewson and Unwin 2007). Examining the reciprocity and transitivity of a network reveals power dynamics within a CoP and CoI in terms of the role and status of participants. C*entrality* measures provide information regarding individual influence and prestige. *Degree centrality* is the number of connections of a node. *In-degree centrality* is the number of incoming ties and *out-degree centrality* the number of out-going ties (Borgatti et al. 2013). A high out-degree has been linked to influence whereas a high in-degree signifies prestige (Hanneman and Riddle 2005). An influential node spreads information by reaching out to other nodes whereas, a prestigious

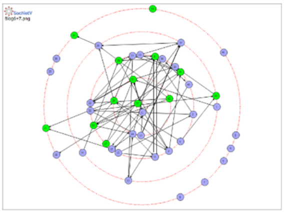
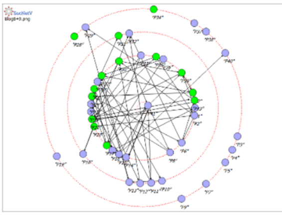
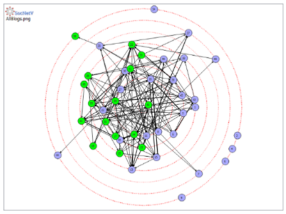
Table 4 Interpretation of sub-group analysis based on CoP and CoI components

SNA construct	CoP	CoI
Cliques	A number of overlapping cliques Overlapping nodes represent brokers/bridges E.g. selective qualitative analysis of contributions by brokers/bridges would assess significance of the contributions towards material and/or conceptual artefacts for shared repertoire of the community.	A number of overlapping cliques. Overlapping nodes represent brokers/bridges E.g. selective qualitative analysis would identify a dominant presence in a specific clique or in brokers/bridges thereby establishing their role in the community.

Table 5 Interpretation of individual power dynamics within a CoP and CoI

SNA construct	CoP	CoI
Reciprocity	High reciprocity indicative of mutual exchange and negotiation of meaning. Lower reciprocity compared to CoI signifying a more hierarchical network in which power resides with key participants	High reciprocity indicative of mutual exchange and potentially integration and resolution phases of CP. Higher reciprocity compared to CoP signifying an equal distribution of power
Transitivity/redundancy	Lower transitivity and redundancy indicative of a community controlled by experts (in the core)	Higher transitivity and redundancy indicative of non-restrictive community in which information flows freely
Centralities	Degree centralities of individuals indicative of individual trajectories. In-degree and out-degree indicative of level of expertise	Individual degree centralities indicative of high SP and potentially CP and TP. In case of a node being a tutor/facilitator, degree centrality represents TP as well

Table 6 Successive cross-sectional and aggregate network over 5-weeks

Weeks 1 & 2		**Weeks 3 & 4**		**Weeks 1 – 5 (Aggregate)**	
					
No. of ties	65	No. of ties	57	No. of ties	152
Average degree	0.036	Average degree	0.032	Average degree	3.5
Centralization	9.21%	Centralization	8.04%	Centralization	5.2%
Components (n>1)	1	Components (n>1)	1	Components (n>1)	1
Nodes in largest component	34	Nodes in largest component	33	Nodes in largest component	38
Cliques (n=3)	2	Cliques (n=3)	2	Cliques (n=3)	45
Core nodes	P10, P35	Core nodes	P14, P41	Core nodes	P2, P10, P35
Reciprocity	5.3%	Reciprocity	3.7%	Reciprocity	7.0%
Transitivity	3.1%	Transitivity	2.1%	Transitivity	3.3%

node attracts interaction from other nodes. Tracking the level of influence and prestige of a node is indicative of the function or role of a node in a network (Rissen and Bottoms 2014). While the selected SNA constructs provide a good indication of the power dynamics within a community, again a detailed investigation would require the support of selective qualitative analysis.

5 Case Study: Evolution of an Online Blogging Community

To illustrate use of the IMF, we present a case study on an online blogging activity, within the LMS, used to create a sense of community amongst first-year students in a human sciences course at a large metropolitan university in Australia. The course ran in semester 1 of 2017 for a total of 13-weeks and included weekly online blogs for 10 weeks (5 non-interactive blogs and 5 interactive blogs). The interactive blogs required students to make a blog post and comment on each other's post within the week. The course was primarily online with 2 optional on-campus days in the 3rd and 9th weeks of the semester. The course included 1 lecturer, 2 tutors and 43 students in all. Fifty percent of the grade was allocated to the e-portfolio and online tasks which included quizzes, two reflections and, the weekly blogs. In line with the key objective of the lecturer to assess the learning process rather than the product, the e-portfolio and online activities including the blogs weighed significantly on the final grade. We used the IMF to examine evolution of the relational network over the 5-week period of interactive blogging. The blogging activity did not include the lecturer and tutors therefore the network consisted of 43 nodes (students only). We demonstrate the effectiveness of the IMF in identifying the type of community formed, if any, based on overall network structure and properties of cross-sectional and cumulative networks.

Sage 1—Preparation of data: Interaction data was extracted from the LMS (Moodle) at the end of weeks 1 and 2 and 3 and 4 to obtain cross-sections of the network, and at the end of week 5, to obtain the aggregated network. The data was coded into matrices in UCINET

6.0. SNA measures were calculated for each cross-section and the aggregate network in UCINET 6.0 and radial diagrams were generated in Social Network Visualizer 2.3.

Stage 2—Static and temporal analysis: Firstly, we examined the radial diagrams of weeks 1 and 2 and weeks 3 and 4 shown in Table 6. The nodes (students) on the extreme periphery represent the isolates, i.e. students who either did not make a blog post or did not receive or post a response to others. In weeks 1 and 2, only 34 (79%) students engaged (interacted) in the blogging activity. This is indicated by the large number of isolates. Within the students that did engage, the network appears dense, with an equal distribution of ties, decentralized and with no clear core-periphery structure. In weeks 3 and 4, 33 (77%) of students engaged in the blogging activity and while the network appears dense, a large number of students are placed on the inner periphery with only one student in the centre of the network therefore, the centralization remains low. However, the ties do not appear to be equally distributed. At this point, based on visual inspection of the radial diagrams, it is difficult to arrive at a preliminary conclusion regarding the type community formed based on parameters in the IMF. Therefore, we need to examine the SNA constructs corresponding with the diagrams. Looking at the SNA constructs in Table 6, we see that both weeks 1 and 2 and weeks 3 and 4 cross-sections have a very low average degree. This is owing to the large number of isolates. If we consider the average degree within the one large component (engaged students), the average degree is relatively high (1.9 for weeks 1 and 2 and 1.7 for weeks 3 and 4). Both networks have only 2 nodes in the core. The core changes from one cross-section to the other indicating legitimate peripheral participation. The reciprocity, indicative of mutual exchange, and transitivity, indicative of information flow and power dynamics are low thereby implying that the network is restrictive. This is expected in a blogging network (see Sect. 4.3). Both networks have low centralization and only 2 cliques. In summary, the networks embody some features of a CoI (high average degree within the large component and low centralization as well as some features of a CoP (evidence of legitimate peripheral participation and low transitivity). The low number of cliques corresponds with neither a CoP or a CoI. Therefore, we conclude that in weeks 1 and 2 and weeks 3 and 4, the blogging activity does not bring the students together to form either a CoP or CoI. We now turn to the aggregate (cumulative interactions over 5 weeks) network to assess the overall community formed, if any, at the end of the blogging activity.

Stage 3—Aggregate analysis: Visual inspection of the aggregate radial diagram and examination of corresponding SNA constructs (Table 6) reveal a dense, equally distributed network with low centralization and small core. There are very few isolates. The high number of cliques indicates mutual exchange between specific students rather than in the overall network as is reflected by the low reciprocity. The low reciprocity and transitivity is expected from a blogging network. Based on the parameters in the IMF, we can conclude that the blogging activity leads to the formation of a CoI overtime.

Stage 4—Qualitative analysis: Having established the presence of a CoI, selective qualitative analysis needs to be conducted to address questions such as: What is the relationship between participation in a CoI, individual properties of key nodes and learning? What is the relationship between individual nodes characteristics and the nature and quality of interactions? What pedagogical conclusions can we draw from our findings? Detailed analysis of the data is ongoing.

For additional detailed case studies on identification of a CoP and CoI using the IMF see (Jan 2018; Jan and Vlachopoulos in press).

6 Discussion

The key motivation behind development of the IMF was to address the lack of quantitative research using the CoP and CoI frameworks in HEOL. The inherent structural similarities between networks and communities logically steered us towards exploring the use of SNA to investigate CoPs and CoIs in HEOL. A detailed review of literature (Jan et al. in press) confirmed the lack of a theoretically grounded framework integrating SNA with the CoP and CoI frameworks. We recognize and acknowledge the limitation of the IMF in that it only considers structural characteristics of a CoP and CoI both of which are much more complex structures with several other properties. However, in terms of structural conceptualization of a CoP and CoI and operationalization of SNA measures, we feel the IMF is a good starting point as it provides an effective lens for structurally differentiating between and identifying a CoP and CoI, a task that has been difficult to date.

Practical implications of the IMF extend to researchers, lecturers/facilitators, instructional, educational and/or learning designers and even students. The IMF, which comprises of the visual illustration (Fig. 1) and four sequential components (Fig. 2), provides an effective methodology for assessing learner engagement during a learning activity enabling appropriately planned intervention. It also allows for a holistic assessment of design elements that may or may not lead to formation of a specific type of community during or after activity completion. For instance, if an activity is designed with the intention of bringing students together to form a CoP, using the IMF, the structure of a cross-sectional network extracted at different points during the activity can reveal if a CoP is in-fact being formed or not. If a CoP is not identifiable, the facilitator can pull specific students (nodes) towards the centre of the network by reaching out to them in the hope of altering the structure and dynamics of the network. The impact of the intervention would of course need to be assessed by looking at the cross-sectional network post-intervention. So, while the actualization of the intended learning design cannot be orchestrated (Wenger 1998), pedagogically informed analytics allows some room for influencing the realization of the intended design. Such a response to emergent conditions falls under the realm of the newly emerging field of designed-based research (Bower 2017).

In terms of limitations, while the IMF reduces the need for qualitative analysis for exploring a CoP and CoI, creating matrices from interactional data from a LMS and generation of the radial network diagrams can be fairly time consuming. However, automating the process of data extraction and manipulation would eliminate this limitation making the framework usable by practitioners other than researchers. We would also like to acknowledge that the IMF does not claim that learning within one particular type of community is better than another, or even that community-based learning is more effective than otherwise. The framework was developed based on the historically established significance of communities of learning. As it stands, the functionality of the IMF is ideally suited to learning design and analytics researchers and practitioners who wish to identify and interpret CoP and/or CoI in HEOL using SNA. To date, the reliability and validity of the IMF has been tested in four case-studies (e.g. Jan 2018). The framework is being tested further in ongoing research.

In conclusion, having articulated the theoretical assumptions of how a CoP and CoI can be explained using SNA, described and demonstrated application and interpretation of selected SNA constructs, and discussed practical applications and limitations of the methodological framework, we propose the IMF as a guide for identification of communities of learning in HEOL.

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Compliance with Ethical Standards

Conflict of interest None.

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