Identifying gatekeepers in online learning networks

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Abstract

The rise of the networked society has not only changed our perceptions but also the definitions, roles, processes and dynamics of online learning networks. From offline to online worlds, networks are everywhere and gatekeepers are an important entity in these networks. In this context, the purpose of this paper is to explore gatekeeping and gatekeepers in online learning networks. In this regard, it will examine the indicators of gatekeeping and gatekeepers, and gatekeepers' roles and functions in learning network formation processes. For the purposes of the research, the paper uses multiple-case design and examines three connectivist Massive Open Online Courses through social network analysis. The findings of the research indicate that betweenness centrality is an important indicator of gatekeeping and gatekeepers. Moreover, gatekeepers have an important role in learning network formation processes and their actions are one of the determiners of the network structure.

Keywords: Brokers, gatekeepers, gatekeeping, online learning networks, Network Gatekeeping Theory (NGT).

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1. Introduction

"The Internet has really democratized ideas. There are no real gatekeepers anymore, because if you have a great idea, and you put it online, people will find it and it will get in front of who it needs to get in front of." Justin Halpern

In the age of digital knowledge, power in a networked society is articulated through networks. Online networks are such a powerful structure that anything that reaches the Internet may reach the world at large (Castells, 2011). In the articulation of power, brokers emerge as an important entity that can control the process. In this context, brokerage is defined as "a process by which intermediary actors facilitate transactions between other actors lacking access to or trust in one another" (Marsden, 1982, p. 202) and a broker is "a person who connects two otherwise unconnected people in a position to manage the information flow" (Ehrlich and Carboni, 2005, p.11). In other words, brokers are entities that can transfer knowledge between networks, subnetworks, or nodes that are not linked directly (Nooteboom, 2003). Brokers and brokerage behaviours can be seen in the structural holes of a network (Burt; 1992; 2005). In these processes, a broker may have one of the following roles: Coordinator, consultant, representative, liaison, or gatekeeper (Gould and Fernandez, 1989).

In the socially constructed Knowledge Management Model, there are four phases. These are knowledge construction, dissemination, use and embodiment (Demarest, 1997). Gatekeepers have functional roles in these phases and they can influence information flow in local and global dimensions (Rychen, 2006; Messeni Petruzzelli, Albino, Carbonara and Rotolo, 2010). Thus, it is important to explore gatekeepers in terms of knowledge management and learning networks. Indicating the importance and influence of gatekeeping, Mark Zuckerberg, CEO of Facebook says: "a squirrel dying in your front yard may be more relevant to your interests right now than people dying in Africa". "At Facebook, relevance is virtually the only criterion that determines what users see. Focusing on the most personally relevant news — the squirrel — is a great business strategy. But it leaves us staring at our front yard instead of reading about suffering, genocide and revolution" (Pariser, 2011, para.8). These ideas reveal the importance of gatekeeping and evoke further questions: Who determines the content which is good for you? Is it you or someone else? In a digital world, do we have the rights to choose what we want? As expressed in Coldplay's song "Fix you", what's the use of "when you get what you want, but not what you need?" (Berryman, Buckland, Champion and Martin, 2005).

2. Purpose of the Research

Based on the above discussions, this paper investigates gatekeepers in learning networks and intends to provide a deeper understanding regarding their roles, positions and abilities. In this regard, the research uses multiple-case design and examines three connectivist Massive Open Online Courses (cMOOCs) through social network analysis. The research seeks for answers to the following research questions:

- What are the indicators of the gatekeeping in learning networks and how can we identify gatekeepers?
- How can gatekeepers affect formation of learning networks?

3. Gatekeepers: Power Controllers

From formal to informal networks, gatekeepers are all around us. Even in physical networks or digitally empowered online networks, nothing has changed: just as in our old small worlds, now we have our new digital gatekeepers and they have the power. Before digitalization, human beings and legal regulations served as our gatekeepers, but in the twenty first century world, algorithms,

software, bots and other digital entities, as well as human beings in online and offline spaces, have also been added to the lists that define gatekeepers. Though the literature provides definitions and explanations about gatekeepers, there are still some issues to explore further: who are the new gatekeepers in a networked digital world? How can we find them in all the complexities of the networks?

Kurt Lewin (1947; 1951), who coined the "gatekeeper" concept, realized that after the Second World War, housewives became the key gatekeepers who control what food enters the "channels" that ultimately bring it from the garden or supermarket into the household and ultimately onto the dining-room table (Roberts, 2005). We are now aware of a gatekeeping that is beyond its first definition made in the Second World War. In today's world, gatekeeping is more a ubiquitous and diverse phenomenon that can be observed in many fields of routine life (Barzilai-Nahon, 2009).

A gatekeeping process involves doing some of the following: selecting, channelling, shaping, manipulating, and deleting information (Laidlaw, 2010). In this regard, gatekeepers can be identified as entities that guard a gate or an individual who controls access. Nodes with these roles are important in any type of network because they have capability to control the knowledge flow and so, to some extent, the ability the shape the network.

Gatekeeping is related to different types of power and it broadly refers to the process of controlling information as it moves through a gate or filter (e.g., selecting news, enforcing the status quo in parliamentary committees, mediating between professional and ethnic groups, brokering expert information) (Barzilai-Nahon, 2009). For the question, "How gatekeeping is related to power?", Carpenter (2014) provides following explanation: "the idea is that power exists not only in broad formal authority to direct the behaviour of others (directive power), but also in appearances that are less obvious: the ability to define what sorts of problems, debates, and agendas structure human activity (gatekeeping power), and the ability to shape the content and structure of human cognition itself (conceptual power)" (Carpenter, 2014, p.11).

Interestingly, as Pariser (2011) indicated, "personalization filters serve up a kind of invisible auto propaganda, indoctrinating us with our own ideas, amplifying our desire for things that are familiar and leaving us oblivious to the dangers lurking in the dark territory of the unknown" (p.15). Technology is a magic, but we also have the dark side of it: "Just Google it!" has become a common cyber-snobbish response to questions that seem too trivial to merit a human conversation. However, is it really an answer? Now that more and more Internet sites are tailoring their services to the idiosyncrasies of individual users, queries for "climate change," "stem cells" and even "pizza" may yield different outcomes for different people. This may be an era when we are increasingly entitled to our own facts — but should we also be entitled to our own search results?" (Morozov, 2011, p.1)

Mass communication and journalism is also a popular field for the gatekeepers and most of the earliest theories of gatekeeping have been developed in this field. Mass communication and journalism viewed gatekeepers as human information filters and identified them particularly as newspaper, radio, and television news editors (Bouhnik & Giat, 2015). In this field, gatekeeping has been defined as, "the process by which selections are made in media work, especially decisions whether or not to admit a particular news story to pass through the 'gates' of a news medium into the news channels." (McQuail, 1987, p.213).

4. Gatekeepers at Online Learning Networks

Open online networks are more than synthetic binary digits, but learning ecosystems that are alive (Bozkurt, Honeychurch, Caines, Maha, Koutropoulos and Cormier, 2016). In this type of ecosystems, centralized wired networks become obsolete, and communication and interaction opportunities that cannot be imagined with wired networks become possible. The sender-to-receiver role is no longer

significant, as the gated could also act as the source of information (Barzilai-Nahon, 2008; Bastos, Raimundo & Travitzki, 2013).

In social network analysis (SNA), gatekeepers hold a critical position between other nodes that are not directly linked (Nooteboom, 2003) and thus, in a network, they are nodes that provide a connection, and serve as a bridge (Haythornethwaite, 1996; Mishra, Cayzer and Madden, 2017) and their critical positions can naturally achieve a certain level of power (Wellman, 1983).

Gatekeepers can be identified with high betweenness centrality (Bavelas 1948; Freeman 1977, 1979; Giuliani and Bell, 2005), which is a centrality metric that shows bridging score of a node (Gould and Fernandez, 1989). However, knowing only which nodes have high betweenness centrality is not enough. For instance, absorptive capacity (Cohen & Levinthal, 1990), and social capital (Boschma & ter Wal, 2007) can be other reasons to be crowned as a gatekeeper. Therefore, entities that hold critical positions as a bridge and dominate communication channels with other attributes can also be referred as gatekeepers (Zhu, Watts & Chen, 2010). Once an entity crowned as a gatekeeper, the collective mechanism attributes the gatekeeping role and gatekeepers carry out their gatekeeping roles (Castells, Monge & Contractor, 2011; Nahon, 2011). In any network, there are two main gatekeeping roles (Metoyer-Duran, 1993):

- The gatekeeper that controls access to information, and acts in an inhibitor capacity by limiting access to or restricting the scope of information.

- The gatekeeper that acts as 'innovator, change agent, communication channel, link, intermediary, helper, adapter, opinion leader, broker, and facilitator'.

However, to fully understand this phenomenon within network context, we should briefly examine theoretical pillars of gatekeepers and gatekeeping.

5. Network Gatekeeping Theory

Network Gatekeeping Theory (NGT) examines power as a main component to understand the interactions in networks (Barzilai-Nahon, 2008, 2009). In NGT, there are four basic construct: gate (the passage point); gatekeeping (the process); gatekeeper (who performs gatekeeping); the gated (on whom gatekeeping is exercised); and gatekeeping mechanisms (the means used to carry out gatekeeping) (Barzilai-Nahon, 2008).

Network technologies have changed identity of gatekeepers and added new values to gatekeeping (Barzilai-Nahon, 2008). NGT claims to explain gatekeepers and gatekeeping on digital networks (Barzilai-Nahon, 2004) which is "a space of information, and conceptualizes the distribution of information and processes of information control. Hence, it enables to analyse centralization in networks, which have a decentralized design, and are grasped in many cases as egalitarian spaces." Accordingly, a network gatekeeper is an entity (people, organizations, or governments) that has the discretion to exercise gatekeeping through a gatekeeping mechanism in networks and can choose the extent to which this gatekeeping is exercised, contingent upon the standing of the gated (Barzilai-Nahon, 2008; Nahon, 2011).

6. Methodology

6.1. Method and Research design

A case study is a systematic collection of information about an individual, a group, or an entire community (Hagan, 1993; Yin, 1994). It can be about a social setting or event in order to gain insight

into its functioning (Schreiber and Asner-Self, 2011). Case studies may use multiple sources of evidence and combine a variety of data collection methods (Gillham, 2000). For the purposes of the study, this research uses multiple-case design (Yin, 1994) to investigate gatekeeping and gatekeepers in learning networks. In this regard, three cMOOCs were examined, as examples of digital learning networks. In data collection and analysing processes, the research employed social network analysis.

Social Network Analysis is used to analyse structural patterns of social relationships (Scott, 1991, Wasserman and Faust, 1994, Wellman and Berkowitz, 1988; Krebs, 2002; Gürsakal, 2009). It provides both quantitative (metrics) and qualitative data (sociogram) to identify, visualize, and analyse the informal personal networks within and between organizations (Müller-Prothmann, 2006; De Nooy, Mrvar and Batagelj, 2011). Based on global and local metrics, networks can be visualized through sociograms in which nodes are represented as points and ties are represented as lines to conceptualize and analyse them. In sociograms, a node can be a living or non-living entity. The interactions, relationships or links among these nodes define ties. In essence, every network is the sum of nodes and ties among them (Bozkurt, 2017).

6.2. Research context

The research examines gatekeeping and gatekeepers in three cMOOCs: Rhizomatic Learning (Rhizo15), Connected Learning 2016 (CLMOOC) and Innovators Mindset 2016 (IMMOOC). Rhizo15 was facilitated for six weeks from April 14 to May 26 in 2015. CLMOOC 2016 was facilitated for five weeks from July 10 to August 6 in 2016. IMMOOC 2016 was facilitated for six weeks from September 17 to October 29 in 2016. All these MOOCs were designed using connectivist learning principles.

6.3. Sampling, Data Collecting, Procedure and Analysis

The samples were chosen from the first weeks of the Rhizo15, CLMOOC and IMMOOC with an assumption that the most densely participation could be observed just after they started. The network data was collected and analysed through NodeXL, which is social network analysis software. Both global and local metrics were calculated and a sociogram was created using local/global metrics. Global metrics were used to describe the learning network, while local metrics were used to identify nodes (cMOOC participants) and subsequently to identify gatekeepers. With a purposeful sampling approach, only those nodes with highest betweenness centrality were chosen and examined as gatekeepers. However, to have a holistic view and compare the metrics, the data of the top ten nodes with the highest betweenness centrality, including the highest one that was identified as the gatekeeper, was provided.

In addition to quantitative network metrics, a qualitative network sociogram was created to identify the gatekeepers' position in the network. Gatekeepers were marked as yellow squares and their ties were marked as blue ties. Other nodes were marked as circles and their colours were assigned randomly, according to the clusters to which they belonged. Their ties were assigned green.

The graph's nodes were grouped using the Clauset-Newman-Moore cluster algorithm (Clauset, Newman & Moore, 2004). The graph was laid out using the Harel-Koren Fast Multiscale layout algorithm (Harel & Koren, 2001). Tie colours are based on tie weight and widths are based on tie weight values. Tie opacities are based on edge weight values. Node sizes are based on betweenness centrality values.

6.4. Limitations and strengths

This research examined gatekeeping and gatekeepers, focusing on the nodes with the highest betweenness centrality in three learning networks and sampled only one node in each network. However, it should be noted that a network could include more than one gatekeeper. Though such an approach can be a treated as limitation, the research used this approach in order to be able to compare the most obvious gatekeepers in three separate cases. The strength of the paper lies in the scope of the research. It has a special focus on learning networks, which is seldom investigated in the related literature.
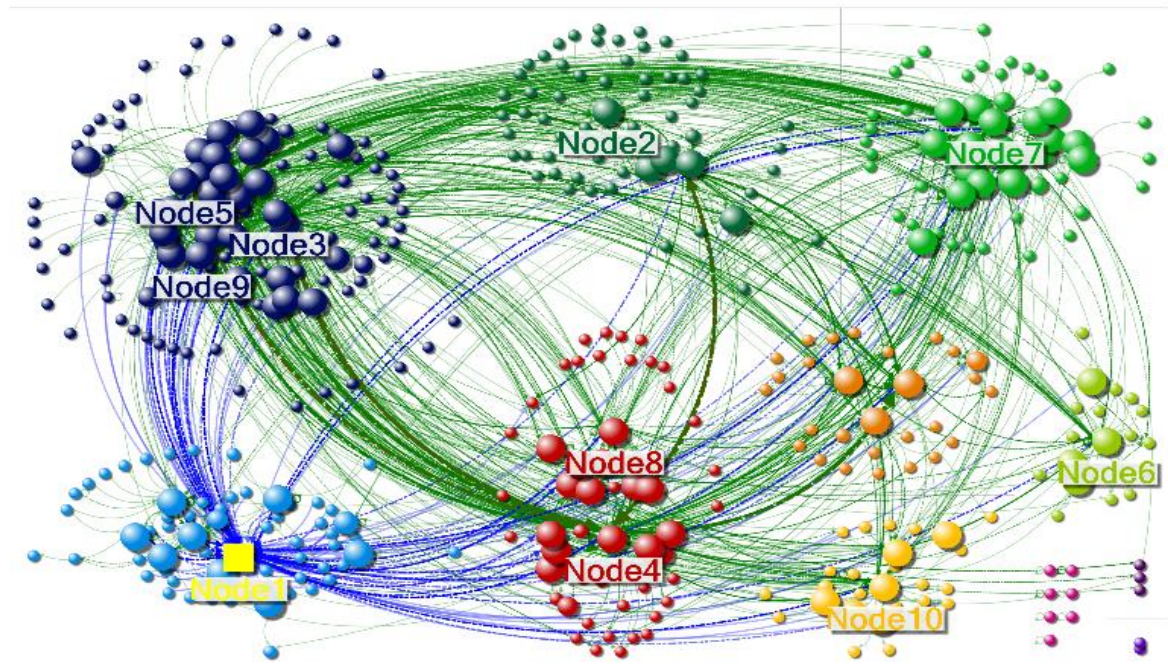
7. Findings and Discussion

This section examines gatekeeping and gatekeepers within the cases of three cMOOCs with a focus on global and local metrics, and their position in sociograms. For each graph, the overall network metrics were calculated including the total number of nodes, ties, reciprocated node pair ratio, reciprocated tie ratio, max. geodesic distance (diameter), average geodesic distance, graph density, and modularity. For the top ten nodes with the highest betweenness centrality, including the one identified as gatekeeper, node metrics such as in-degree, out-degree, betweenness centrality, closeness centrality, eigenvector centrality, PageRank, clustering coefficient and reciprocated vertex pair ratio were calculated and reported.

7.1. Case I: RHIZO15

The first week of the Rhizo15 network consisted of 431 learners (nodes) and 4843 interactions occurred among them. Maximum geodesic distance was 6, while average geodesic distance was 2,8656. Graph density was 0,0089 and modularity was 0,1497. Based on community structure classification (Smith, Rainie, Shneiderman and Himelboim, 2014), the network demonstrated a connected/unified tight crowd community structure (Figure 1).

When the Rhizo15 network is examined in terms of gatekeeping, it can be seen that the node with high betweenness centrality, that is to say the gatekeeper (yellow square with blue ties) that holds a position as a bridge is able to control knowledge flow within the learning network. Furthermore, apparently the node identified as gatekeeper has ties with most of the other nodes with high betweenness centrality (Table 1). When examined, it can be seen that the node with the highest centrality (39446,56) outnumbers other nodes only in terms of betweenness centrality. Other metrics, such as closeness centrality (0,00128), eigenvector centrality (0,023999), PageRank (16,84366), clustering coefficient (0,053857), reciprocated node pair ratio (0,14876) are lower than other nodes. However, as can be seen in Table 1, PageRank slightly differs when compared to other nodes and thus it can be evaluated as relatively high.

Social media network connections among Twitter users for # by Aras BOZKURT

Graph Metric	Value	Graph Metric	Value
Graph Type	Directed	Max. Geodesic Distance	6
Nodes	431	Average Geodesic Distance	2,8656
Total Ties	4843	Graph Density	0,0089
Reciprocated Node Pair Ratio	0,2264	Modularity	0,1497
Reciprocated Tie Ratio	0,3692		

Figure 1. Rhizo15 sociogram and network metrics.

Table 1. Rhizo15 node metrics
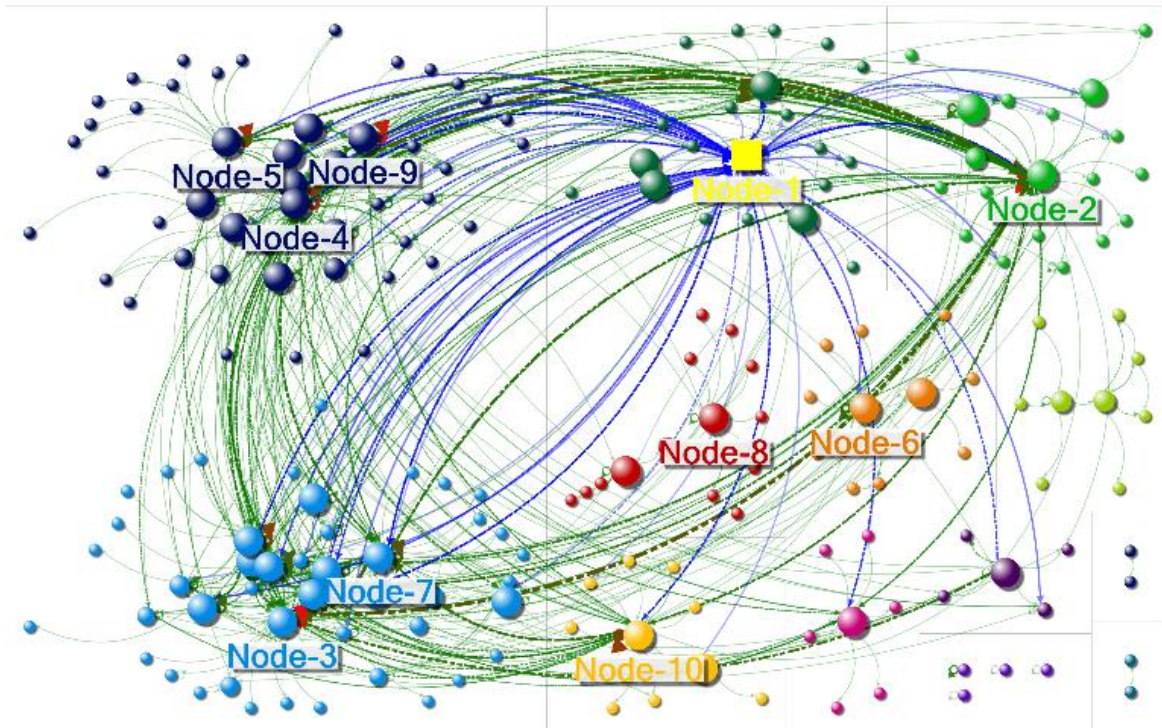
Node	In-Degree	Out-Degree	Betweenness Centrality	Closeness Centrality	Eigenvector Centrality	PageRank	Clustering Coefficient	Reciprocated Node Pair Ratio
Node1	110	31	39446,56	0,00128	0,023999	16,84366	0,053857	0,14876
Node2	71	8	37403,27	0,001125	0,011608	16,85903	0,042058	0,069444
Node3	72	98	33170,93	0,001332	0,024986	15,82341	0,056232	0,4
Node4	52	101	23893,1	0,001326	0,024691	12,9094	0,073749	0,451923
Node5	55	58	15733,55	0,001279	0,02222	10,4729	0,099541	0,321429
Node6	21	38	12781,43	0,001155	0,012786	6,420084	0,151163	0,295455
Node7	32	64	11554,6	0,001222	0,019343	8,852193	0,112475	0,323944
Node8	27	45	10720,07	0,001181	0,015131	7,10688	0,140784	0,372549
Node9	44	52	10229,44	0,00113	0,017975	8,51627	0,108548	0,402985
Node10	28	36	9008,074	0,00116	0,014606	6,138662	0,1657	0,347826

Gursakal, N. & Bozkurt, A. (2017). Identifying gatekeepers in online learning networks. *World Journal on Educational Technology: Current Issues. 9*(2), 75-88.

7.2. Case II: CLMOOC 2016

The first week of the CLMOOC network consisted of 200 learners (nodes) and 1886 interactions among them. Maximum geodesic distance was 5, while average geodesic distance was 2,8120. Graph density was 0,0179 and modularity was 0,1621. Based on community structure classification (Smith, Rainie, Shneiderman and Himelboim, 2014), the network demonstrated a connected/unified tight crowd community structure (Figure 2).

When the CLMOOC network is examined in terms of gatekeeping, it can be seen that the node with the high betweenness centrality, that is to say the gatekeeper (yellow square with blue ties) that holds a position as a bridge, is able to control knowledge flow within the learning network. Furthermore, as in the first case, the node identified as gatekeeper has ties with most of the other nodes with high betweenness centrality (Table 2). When examined, it is clear that the node with highest centrality (6660,032) has also the highest PageRank (8,312163), which is similar to situation in the Rhizo15 case. However, when compared, it can be seen that closeness centrality (0,003067), eigenvector centrality (0,036357), reciprocated node pair ratio (0,491228) and clustering coefficient (0,113722) are slightly lower than other nodes.

Graph Metric	Value	Graph Metric	Value
Graph Type	Directed	Max. Geodesic Distance	5
Nodes	200	Average Geodesic Distance	2,8120
Total Ties	1886	Graph Density	0,0179
Reciprocated Node Pair Ratio	0,2854	Modularity	0,1621
Reciprocated Tie Ratio	0,4441		

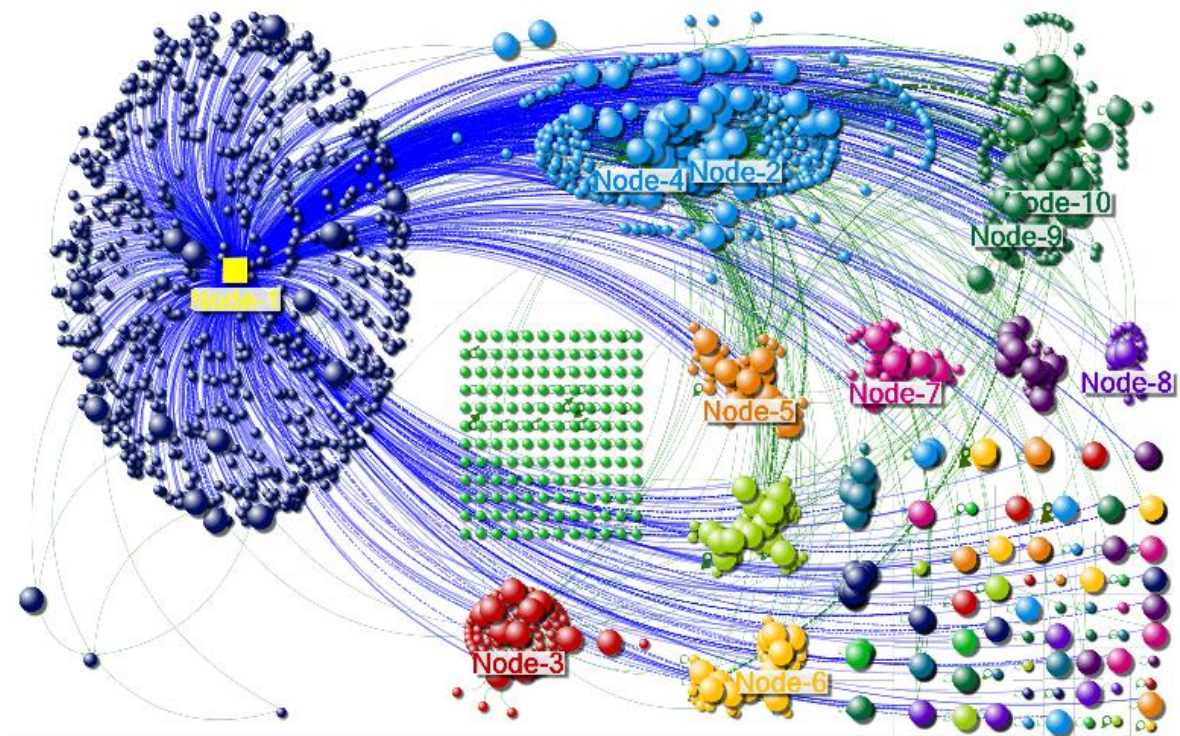Figure 2. CLMOOC16 sociogram and network metrics.

Table 2. CLMOOC16 node metrics

Node	In-Degree	Out-Degree	Betweenness Centrality	Closeness Centrality	Eigenvector Centrality	PageRank	Clustering Coefficient	Reciprocated Node Pair Ratio
Node1	38	49	6660,032	0,003067	0,036357	8,312163	0,113722	0,491228
Node2	35	57	6284,707	0,003226	0,038884	8,246993	0,113842	0,5
Node3	41	21	5396,331	0,003058	0,03285	7,060767	0,134779	0,22449
Node4	32	51	4620,078	0,003096	0,037969	7,47931	0,130519	0,446429
Node5	12	26	3715,968	0,002604	0,018431	4,962133	0,153439	0,285714
Node6	9	9	3522,166	0,00237	0,00943	2,939741	0,166667	0,230769
Node7	28	29	3289,72	0,002793	0,02915	5,491242	0,178812	0,410256
Node8	7	11	3057,991	0,002331	0,008242	3,603296	0,085714	0,066667
Node9	16	26	2961,973	0,002725	0,023193	4,732101	0,193548	0,290323
Node10	18	32	2745,598	0,002762	0,028419	5,367332	0,172119	0,263158

7.3. Case III: IMMOOC 2016

The first week of the IMMOOC network consisted of 2003 learners (nodes) and 4706 interactions among them. Maximum geodesic distance was 8, while average geodesic distance was 2,7422. Graph density was 0,0007 and modularity was 0,4190. Based on community structure classification (Smith, Rainie, Shneiderman and Himelboim, 2014), the network demonstrated an in-hub and spoke broadcast community structure (Figure 3).

When the IMMOOC network is examined in terms of gatekeeping, it can be seen that the node with high betweenness centrality, that is to say the gatekeeper (yellow square with blue ties) that holds a position as a bridge, is able to control knowledge flow within the learning network. However, different from the Rhizo15 and CLMOOC cases, its ties are generally in one-way in-hub direction. As reported in Table 3, the node's in-degree metric is 1132 while its out-degree is 69. The imbalance between in-degree and out-degree also affect community structure (see Figure 3). Moreover, as in the first and second cases, apparently the node identified as gatekeeper has ties with most of the other nodes with high betweenness centrality. However, it is also salient that the difference in betweenness centrality is greater than other cases examined (Table 1 and 2) and greater than other nodes in the same network (Table 3). When examined, the node with highest betweenness centrality (2795182) has the highest closeness centrality (0,000393), eigenvector centrality (0,036357), PageRank (352,2635), while clustering coefficient (0,000663) and reciprocated node pair ratio (0,036301) metrics are lower than the other nodes.

Social media network connections among Twitter users for #immooc by Aras BOZKURT

Graph Metric	Value	Graph Metric	Value
Graph Type	Directed	Max. Geodesic Distance	8
Nodes	2003	Average Geodesic Distance	2,7422
Total Ties	4706	Graph Density	0,0007
Reciprocated Node Pair Ratio	0,0438	Modularity	0,4190
Reciprocated Tie Ratio	0,0841		

Figure 3. IMMOOC sociogram and network metrics.

Table 3. IMMOOC node metrics

Node	In-Degree	Out-Degree	Betweenness Centrality	Closeness Centrality	Eigenvector Centrality	PageRank	Clustering Coefficient	Reciprocated Node Pair Ratio
Node1	1132	69	2795182	0,000393	0,026096	352,2635	0,000663	0,036301
Node2	225	54	387627,8	0,00027	0,005619	62,53705	0,006677	0,116935
Node3	107	3	270780,3	0,000245	0,001633	35,26082	0,00291	0,009346
Node4	227	24	270454,2	0,000271	0,006454	55,81398	0,008235	0,064103
Node5	54	8	91394,2	0,000255	0,002134	14,97887	0,028736	0,034483
Node6	31	1	74595,97	0,000233	0,000942	10,32499	0,008046	0
Node7	24	15	63169,92	0,000242	0,001297	9,85708	0,029412	0,057143
Node8	26	3	62549,95	0,00024	0,001146	8,02371	0,031339	0
Node9	28	3	55153,86	0,000237	0,001198	8,121039	0,025641	0,074074
Node10	28	12	54527,52	0,000247	0,001646	8,368383	0,053782	0,085714

Considering the first research question "What are the indicators of the gatekeeping in learning networks and how can we identify gatekeepers?", the research findings indicate that betweenness centrality is a strong indicator of gatekeeping and can be used to identify gatekeepers. This confirms previous explanations, which claim that gatekeepers can be identified through betweenness centrality (Bavelas 1948; Freeman 1977; 1979; Giuliani & Bell, 2005). However, as can be seen in three cases, PageRank, which is a way of measuring the importance and influence of a node by analysing their ties/links (Brin & Page, 2012), can be another indicator to identify gatekeepers. This finding evokes further questions. Google's PageRank algorithm focuses on the links of a node. Therefore, in terms of digital identity formation (Bozkurt & Tu, 2016) and gatekeepers' relationships as digital identities in social network sites, that can be linked social capital, in other words, number of the followed and followers in and out of a learning community. When these links considered as Social Capital (Coleman, 1988), followers of the nodes in this case can be another variable, which may increase the influence of a node and therefore help nodes emerge as a gatekeeper. However, this requires further empirical investigations.

In terms of the second research question, "How can gatekeepers affect formation of learning networks?", the research findings reveal that the gatekeepers' roles designate network type and interaction level within the community. This finding coincides with Metoyer-Duran's (1993) explanations, who argues that a gatekeeper has the ability to increase or decrease the information flow. As can be seen in the Rhizo15 and CLMOOC cases, the gatekeeper can act as catalyst of the network by building diverse ties in the learning network resulting with a highly reciprocated node pair ratio, which also has an effect in graph density metric. As can be seen, the network structure of the Rhizo15 and CLMOOC learning networks emerge as a connected/unified tight crowd community structure. However, the IMMOOC network emerges as an in-hub and spoke broadcast community structure.

As an additional remark, it is also worth noting that in the Rhizo15 and CLMOOC learning networks, the power is distributed across the network (Table 1 and 2). On the other hand, in the IMMOOC learning network, the power is mostly centralized around a single node (Table 3). The density (interaction level) in the Rhizo15 and CLMOOC learning networks are 0,0089 and 0,0179 respectively, while it is 0,0007 in the IMMOOC learning network. Based on patterns about power distribution and density metrics, it could be said that distribution of the power in learning networks can lessen the negative effects of gatekeeping.

Finally, even though this research specifically focused on nodes in learning networks, it is also important to examine ties in terms of gatekeeping. Though such a topic is beyond the scope of this paper, it is considered as a future research avenue that can be examined under the lens of connectivism. Connectivism is the learning theory for the digital age (Siemens, 2004). It has a special focus on connecting specialized information sets, and it claims that the connections that enable us to learn more are more important than our current state of knowing. According to Connectivism, "the pipe is more important than the content within the pipe". It further claims, "Learning is a process of connecting specialized nodes or information sources". Connectivism highlights the importance of the pipes and conduits within the SNA perspective and the importance of the ties. Accordingly, not all ties have the same capacity, and ties that connect important hubs or subnetworks have more importance than other ties in the network. Supporting this notion, Mueller and Broekel (2014) suggested that not only nodes but also ties could be gatekeepers because each tie connects different nodes and thus has different capacities. In this regard, ties can be identified as gatekeepers by using the tie betweenness centrality metric. They further stressed that ties that are connected to gatekeepers are characterized by cognitive and social proximity and tend to show superior capabilities in establishing links to other cognitively or socially proximate gatekeepers.

8. Conclusion and Future Implications

First of all, betweenness centrality is an important indicator of gatekeeping and gatekeepers. On the other hand, PageRank metric can be evaluated as another indicator that demonstrates a node's importance and influence. If a node's existing ties are perceived as social capital, which can be related to the importance and influence of the gatekeeper, social capital can be seen as a peripheral factor.

Secondly, gatekeepers can affect a learning network positively or negatively. Gatekeepers' behaviour in mutual interactions, in other words the degree of reciprocity, determines whether a gatekeeper would be a catalyst or inhibitor in a learning network, which naturally determines the structure of any network, or climate of any learning ecology. The gatekeepers' role as catalyst or inhibitor defines the interaction level in a learning network, which is an important issue in social learning settings.

Ostensibly, in a digital learning network, gatekeepers and gatekeeping differ from their traditional meanings. Traditional definitions impose a predetermined negative role to gatekeepers. On the other hand, the findings of this research demonstrate that gatekeepers' capacity, as a catalyst or an inhibitor, which is not a predetermined role but one that emerges through the network formation processes.

In a scale-free network, it is expected to see a long tail distribution of the nodes. Thus, it is natural to see gatekeepers in any scale-free network. That's why learning designers should develop strategies to benefit from gatekeepers as a catalyst. Based on the analysis of this research, it can be said that distribution of the power across the network, distributed learning opportunities and decentralized learning design, may crown gatekeepers as a catalyst of the learning processes rather than an impetus. A distributed and decentralized approach may lessen dependency on gatekeepers in the information flow process, make the learning network more robust and increase interaction density and reciprocity in a learning network.

Gatekeepers indisputably have a vital role in a learning network. They can emerge as a bottleneck that limits information flow or as an opening that increases it. They can also make an innovative idea viral across the networks that are assumed to be important in terms of the dissemination of information. Within this perspective, the following implications can be considered for future research. First, the effect of social capital as a variable, which may determine gatekeepers' power, can be further investigated. Secondly, there is a need for correlational studies to find an explanation for what other metrics may consider to be an indicator of gatekeeping and gatekeepers. Thirdly, in addition to nodes, networks, subnetworks or ties can be examined in terms of gatekeeping, in order to provide a deeper understanding of the phenomenon.

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