

Identifying key actors for technology adoption in higher education: A social network approach

Negin Mirriahi University of British Columbia

Shane DawsonUniversity of British Columbia

Debra Hoven

Athabasca University

Higher education institutions are increasingly implementing strategies and practices aimed towards enhancing learning for the future by integrating educational technologies with classroom instruction. Despite the notable affordances these technologies bring to the learning context, there continues to be some resistance within the academy. Senior higher education administrators or leaders are frequently challenged with developing novel strategies to influence technology adoption. Prior studies relating to technology adoption and diffusion have emphasized the importance of collaboration, mentorship, and communities of practice in influencing the level of technology acceptance. Research in social networks has also shown that key actors within a network can assist with the dissemination of information. This case study investigated the relationship between the position of instructors within their departmental social network and their level of technology adoption to begin to identify strategic access points for facilitating technology adoption within higher education.

Keywords: technology adoption, social networks, higher education

Introduction

Educational technology has been readily available to enhance and supplement teaching and learning practice for the past several decades (Conole, 2010). From the drill and practice exercises in the early days of computer-assisted technologies in the 1970s and 1980s to the growth of educational video and audio during the 1990s, instructors have had a suite of learning technologies available to better complement their pedagogical approaches (Salaberry, 2001). Recent developments in web-based communication and mobile technologies, in particular, have further extended and added to the advantages technology integration can bring to education such as increased flexibility of access and student engagement (Chen, Lambert, & Guidry, 2010). In parallel, higher education leaders are now faced with the challenge of responding to the rapidly evolving global education market and learning needs of the contemporary student body and determining ways of extending educational opportunities beyond the traditional classroom (Hagel, Brown, & Davidson, 2010). For instance, the growth of technology mediated learning opportunities through the University of Phoenix and more recently Edx or MITx and coursera has forced the more traditional institutions to rethink their technology approaches and potential student market.

Senior higher education administrators and leaders have focused on technology integration as a way to meet the demands associated with a global education market and competition (Conole, 2010). Despite the strategic leadership and support, there continues to be resistance across many campuses (Roberts, 2008), an issue that senior higher education administrators and leaders are required to address by finding ways that technology can best be diffused and accepted by individual instructors (Abrahams, 2010). Numerous social, cultural, and sociotechnical factors can influence an instructor's decision to use a particular technology for their teaching and learning practice. For instance, Mwaura's (2003) study, investigating technology adoption of faculty members who attended a technology workshop, revealed that collaboration and mentorship amongst instructors influenced their future acceptance of a particular technology. Similarly, Oncu, Delialioglu, and Brown's (2008) study of the factors that influence mathematics instructors to adopt technology, discovered that when instructors meet with colleagues who are technically advanced, they begin to relate the potential of learning technologies to their own practice. As Kopcha (2008) posited, instructors who are technologically advanced can act as mentors and advocates of technology by sharing materials and experiences with their peers. By acting as a role model to their peers, these innovators or early adopters of technology can help support and advance the strategic initiative of their institutions (Roberts, 2008).

While adopters of learning technologies can share and promote ideas and support amongst their colleagues, it is critical that their status within the peer network is perceived as a role model or educational leader. Instructors who do influence the teaching strategies of their colleagues are frequently regarded as leaders within their immediate network of instructors (de Lima, 2008). To better facilitate technology adoption, senior higher education administrators can therefore turn to the instructors with technology expertise and leadership or influencing qualities, to raise awareness of the affordances of educational technology and share strategies with their colleagues by establishing communities of practice. While, COPs have now long been in existence and promoted extensively in the professional development and learning and teaching sphere, there remains the complexity of readily identifying those adopters that demonstrate the potential for influencing peers within their social network and assessing the level and sophistication of their technology adoption.

Communities of Practice

A community of practice includes professionals who share a common concern or passion about a subject and who wish to interact with one another to share ideas and enhance their knowledge (Wenger, McDermott, & Synder, 2002). Learning about new concepts or strategies, such as integrating technology with teaching practice, can often occur when instructors come together and form a community of practice that involves both those who are technologically advanced and those who have less experience with technology. According to Lave and Wenger (1991), learning occurs when newcomers to a community of practice move from peripheral participation to full active participation at the core of the community. Hence, those who are at the center of a community of practice are involved in collectively learning and building upon previous knowledge as they continue to develop and refine their practice (Wenger, 1998). Either through self-selection or after being invited by a colleague, members of a community of practice meet to develop and promote best practices or to solve a problem together. While such interactions help foster the sharing of successful teaching practices, instructors also prefer to have such conversations with those who they have known for some time and with whom they feel comfortable (Roxa & Martensson, 2009). Trust between colleagues is critical for meaningful and open conversations to take place without negative judgment (Niesz, 2007), thereby prompting further collaboration and tacit knowledge creation (Hagel et al., 2010). A community of practice of instructors led by those who are technologically advanced and considered trustworthy by their peers can, therefore, help advance the integration of technology with pedagogy. In order, to enhance the integration of technology across an institution, education leaders need to easily identify not only the technology pioneers to lead such communities of practice, but also those who have also established trusting relationships with their colleagues that put them in a position of influence. Assessing individuals' positions in their community of practice may help identify the roles that different community members play in their network and the relationships they have with one another (Schlager & Fusco, 2003).

Social Networks, Emerging Leaders, and Thresholds

Social network analysis can act as an effective approach for identifying potential actors in a network that can facilitate the dissemination of information about new technologies and therefore seed and promote adoption. A social network is comprised of individuals who are tied to one another in a "mesh of connections" (Scott, 1988, p. 109). Such ties or connections represent with whom an individual interacts within a network while an individual's position in that network shows the degree that the individual acts as a vector of information from one side of the network to another. The professional social networks of the instructors therefore tend to include colleagues with whom they have a positive rapport and whose opinions they value highly. Identifying the ties between different members of an organization, such an academic department, can show which instructors emerge as leaders or who perform the role of transferring information across a departmental network. According to De Lima (2008), network centralization measures how much a social network is focused around one particular instructor who can emerge as the leader or hold an influential position. Instructors who are most central in a whole social network tend to have leadership qualities (De Lima, 2008), since others trust and value their opinions and approach them for advice or suggestions (Niesz, 2007).

While an individual's centrality in a whole or partial network indicates their potential importance in the department as a leading figure, their network threshold explains how likely they are to be influenced by the behaviours of others. A network threshold refers to an individual being influenced to change a behavior or decision based on the number of colleagues or connections in a network that behave a certain way (Chen et al., 2009). Individuals who are influenced to change a behavior after many others around them have modified their approach are considered to have a high network threshold while those who are less influenced by others have low network thresholds. Valente (1996) made a connection between individuals' network thresholds and their rate of technology adoption according to Rogers' Diffusion of Innovations Model. Rogers' (1995) model

indicates that individuals fall within five stages of technology or innovation adoption: innovators, early adopters, early majority, late majority, and laggards. According to Rogers, the majority of individuals fall within the early or late majority of technology or innovation adoption. As Valente (1996) posits, these early and late majority individuals are influenced to adopt a technology after others have tried it and, therefore, have a high network threshold. Conversely, the innovators, a small proportion of the population, are less influenced by others and are keen to be one of the first to try out a technology. Hence, they have low network thresholds.

Situated in social network theory, this study investigated patterns in social networks to discover any trends between the positions of instructors in their departmental network, their tendency to adopt technology, and how information spreads across the department. Social network theory is most appropriate for studies that explore the relationships and connections between various individuals in an organization or department and the way that information flows among them (Haythornthwaite, 1996). Exploring the relationships between instructors and their network thresholds can determine the "overall web of influence relations that exist within their department" (de Lima, 2008, p. 166), which may help identify those instructors who have this influencing role or potential for it.

Methods

The design of this case study intended to identify the relationship between each instructor's position in a departmental social network and their technology adoption decisions in order to determine how information flows between participants. A case study approach was used in order to gather and analyze rich and deep descriptions about the professional social networks of each of the participants in the study. In addition, since this study focused on discovering the social networks of instructors in one particular educational institution and who taught in specific academic disciplines, as discussed in the next section, a case study was an ideal methodology for this focus, in this context (Eisenhardt, 1989).

Research Setting & Participants

This study took place in a large higher education institution in North America with approximately 47000 students and 3700 faculty members. Instructors across three academic departments were invited to participate in the study. The three academic departments were situated in the language disciplines and were selected for the high level of educational technology evident in their classroom instruction. These departments had previously played an integral role in developing computer labs to assist students in oral and listening practice. They had actively used the learning management system, Blackboard Vista, for some years, to further extend students' oral skill practice through improved integration of audio and video resources and activities. This preliminary study aimed to uncover any inconsistent or contradictory trends across the social networks of the three departments. In order to gain the most complete picture possible of the departmental social networks, all language instructors in the three departments (N = 75) were purposively invited to participate. There was an overall response rate of 31%, however, the rate was inconsistent across the departments with Department A having a significantly lower response rate (13%) than Department B (44%) and Department C (41%). The low response rate for Department A was considered when drawing broader conclusions from the study. In addition, some of the participants were course or program coordinators as well as instructors in their respective departments. Their role in the department was taken into consideration during the data analysis, to determine if it affected their overall centrality in the network analyses.

Data Collection

A combination of observational, pre-interview questionnaire, and interview data was collected in this study. In order to identify any behavioural trends across the departmental social networks and to calculate individual network threshold, it was necessary to determine the extent and diversity of technology adoption. Observational data, therefore, was collected from the learning management system course environments of the participants for all their classes taught at the one institution in 2010 and 2011. The data provided insight into the total number of technologies adopted and based within the learning management system by the study participants. In addition, in-person interviews were conducted with each participant in order to identify any further potential technologies that were not associated with the institutional LMS. Semi-structured interviews, rather than surveys were used to collect this data, since interviews provided an opportunity for the participants to elaborate on the reasons for their choice of other technologies, rather than some of the tools available through Blackboard Vista (Cohen, Manion, & Morrison, 2007; Rapley, 2001). The interviews were audio recorded and transcribed and transcriptions were sent to the participants to ensure the accuracy of the content prior to analysis.

In order to build a picture of the departmental social networks, participants were asked to complete preinterview questionnaires to provide information about the colleagues that they speak to about technology and the frequency of such discussions. Following recommendations by Stork and Richards (1992), a roster of names of their fellow instructors in their academic department was provided to help reduce the likelihood of forgetting or overlooking certain relationships. Furthermore, the pre-interview questionnaire asked instructors to indicate how they perceived their rate of technology adoption according to Rogers' (1995) Diffusion of Innovations Model. The instructors' assessment of their technology adoption assisted with evaluating their network threshold. These data were later analysed in combination with the results of the instructors' network centrality to determine the existence of any statistically significant relationships.

Data Analysis

Observational and interview data were analyzed through content analysis which involved coding and categorizing concepts derived from the written data (Cohen et al., 2007) and developing an aggregation and tally of these (Stake, 1995). Qualitative content analysis software, Atalas.ti, was used to generate codes emerging from the observational notes and the interview transcripts and to create thematic categories. Information gathered from the pre-interview questionnaires concerning with whom the participants spoke regarding technology in their departments was analyzed through social network analysis. A social network analysis and visualization software application, Gephi, was used to determine the position of the participants in their department and develop network diagrams (sociograms) indicating the relationship ties and information flow between individual actors. Figure 1, below, illustrates a social network comprised of eight actors each represented by a single node. The lines between the nodes illustrate connections (relationships) between individuals, while the size of the node represents the number of relationship ties (degrees) they have established in the network structure.

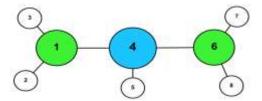


Figure 1: A Network View showing Betweenness Centrality

As seen in Figure 1, the large blue node (number 4) is positioned in the centre of the network. This individual connects with the actors on the left and right side of the network. In other words, information discussed between individuals on one side of a network can flow to those on the other side through this intermediary actor (number 4). According to Freeman (1978), individuals in such positions with high betweenness centrality can influence others by "withholding or distorting information in transition" (p. 221). Hence, analyzing and comparing the location or centrality of instructors in their departmental networks can uncover behavioural patterns prevalent amongst different groups of instructors. As part of the analysis, centrality measures were calculated based on the available network data and then correlated with the participants' total technology adoption, using the Pearson correlation, to determine the extent to which a participant's centrality was proportional to their technology adoption. Statistical software, SPSS, was used to measure the Pearson correlation and identify if the correlation was statistically significant.

Results and Discussion

Prior to investigating the social networks, data was collected through the interviews and observations of the participants' learning management system course environments to identify the extent of technology adoption within each department. This information would later be used during the social network analysis phase to determine patterns and centrality positions of individuals based on their level of technology adoption. The following section reports on the technology use of each participant. For the purpose of this study, technology refers to the specific tools available within the LMS, such as online discussion boards and quizzes, as well as other technologies including blogs, wikis, and digital media that may reside outside of the LMS environment.

Technology Use

Observational data from the learning management environments of the participants was used to indicate the tools each participant had adopted for their classroom instruction. A full mark was given to each type of tool

that each participant had chosen to use at least once. Since observational data was limited to the LMS, interviews were required to reveal any other technologies the participants had adopted for their teaching purposes. These other technologies were coded and categorized to determine the total number of technologies that each participant used. Table 1 presents the observational and interview data concerning the total number of technologies adopted by each participant.

Table 1: Total Technology Adoption of Each Participant

Department A				Department B				Department C			
ID	Total	Vista	Other	ID	Total	Vista	Other	ID	Total	Vista	Other
c1A	8	6	2	c1B	4	3	1	i1C	9	7	2
i2A	12	7	5	i2B	6	4	2	i2C	6	2	4
i3A	4	3	1	c3B	5	3	2	i3C	2	1	1
i4A	3	0	3	i4B	4	3	1	i4C	9	6	3
				i5B	7	3	4	i5C	5	2	3
				i6B	8	6	2	c6C	5	4	1
				i13B	6	5	1	c7C	11	7	4
								i8C	5	5	0
								i9C	9	7	2
								i10C	8	6	2
								i11C	4	3	1
								i12C	9	8	1

As presented in Table 1, there is a broad range of technology adoption across each of the departments. Knowing where each participant falls within the technology adoption range will help to reveal any patterns or trends emerging from the social network analysis, the focus of the following section.

Centrality in Social Networks

Data collected on the pre-interview questionnaires was used to determine the partial social network within each academic department. This information, along with the data reported in Table 1 on technology use, was imported into the social network analysis and visualization software, Gephi, and the network centrality of each participant in their respective departments were calculated. Using the Pearson correlation, centrality measures were correlated with all of the participants' technology adoption scores. However, none of the centrality measures had any statistically significant correlation with technology adoption scores (p > 0.05). However, while the instructors in Department C were encouraged to develop their own LMS environments, selecting the technologies to adopt for themselves, the instructors in departments A and B tended, for the most part, to teach using the LMS environments created by their language coordinators. The centrality and technology scores for the participants in these two departments, therefore, were correlated together (N=11) as shown in Table 2.

Table 2: Correlation between Technology Adoption and Centrality for Departments A and B

	Closeness Centrality	Betweenness Centrality	Degree Centrality
Pearson Correlation	588	.641*	.407
Significance (2-tailed)	.057	.034	.214

^{*} Indicates statistical significance (p < 0.05)

As presented in Table 2, there is a positive significant correlation observed relating the betweenness network centrality with an individual's level of technology adoption. Betweenness centrality refers to the extent to which a participant in a network connects other parts of a network together. Betweenness can be seen to represent characteristics of a 'broker' or 'gatekeeper' of information (Scott, 2007). No significant correlation was observed between technology adoption and neither closeness nor degree centrality. Closeness centrality refers to the distance between the participants in a departmental network while degree centrality refers to the total number of colleagues each participant speaks with about technology.

When delimiting the data into specific departments the correlational trends did not hold true for the third department, Department C. No significant correlation between technology adoption and centrality was observed for the participants in this department (N = 12). Social network analysis of each department separately, as presented in the following section, will illustrate the trends between technology adoption and betweenness

centrality and will shed light on different correlational trends cross the departments.

Betweenness Centrality and Technology Adoption

Individuals with a high betweenness centrality are commonly referred to as the "gate keepers" of information due to their linking position in a network. Burt (1992) describes this linking position as bridging a structural hole. In essence, if the individual were absent from the network, a gap in the overall network structure would exist. Hence, individuals demonstrating a high betweenness score tend to fill this void by brokering information across the network. Such individuals can control how information travels to others (Freeman, 1978) and, subsequently, have greater social influence over others in their network (Brass, 1984). To determine the possible influence of participants' betweenness centrality on technology adoption, the social networks of each department, along with data on the technologies used by the participants, were analyzed. In addition, how the participants perceived themselves on Rogers' (1995) Diffusion of Innovation scale and, therefore, their network thresholds was considered when determining the potential impact of their conversations. Each department is discussed in turn, followed by discussion of the overall results.

Department A

Figure 2 illustrates the betweenness centrality of participants in the social network of Department A. The nodes represent the four participants as well as the various colleagues the individual instructors mentioned that they talk to about technology. However, as mentioned earlier, several members of this department chose not to participate in the study. These non-participating members are indicated with an asterisk beside their identifying code. The number in brackets next to the participants' non-identifying code represents the total number of technologies that they have adopted, as previously reported in Table 1.

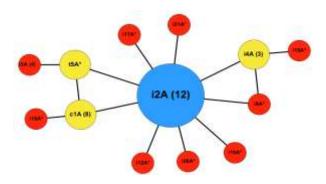


Figure 2: Partial social network of Department A

The lines between each of the nodes in Figure 2 illustrate a connection between each colleague. Since there is a lack of information regarding the types of conversations had by non-participants with those who did participate, there may be more connections than those illustrated above. The size and colour of the nodes visually represent the betweenness centrality of each node or instructor in the network with larger nodes representing higher betweenness centrality. For instance, i2A, represented by the large blue node in the centre of the sociogram has the highest betweenness centrality in this social network. This instructor talks to nine people about technology, three of whom have conversations with one other person. Hence, the conversations that i2A has with those represented by the yellow nodes could potentially affect the conversations between the yellow and red nodes. Moreover, i2A has adopted the most technology in this department, 12 technology applications or tools in total. As presented in Table 2 earlier, as a participant's technology adoption score rises, their betweenness centrality score also rises. Two colleagues in the department, c1A and i3A, also support this correlation pattern. These two instructors have adopted proportionately less technology and also have a proportionately lower betweenness centrality as illustrated by the large blue node in the centre of Figure 2, compared to the smaller red node at the left. Participant, i4A, the yellow node at the right of the figure, however, represents an exception to the correlation trend, with a similar betweenness centrality to c1A, yet has adopted much less technology.

An analysis of the participants' technology adoption from the observational and interview data collection and their betweenness centrality helps uncover the potential impact of the conversations between the different colleagues. For instance, i2A who, on the pre-interview questionnaire, indicated being the first to try a technology (i.e. an innovator) actively uses blogs. A colleague, i4A, who speaks with i2A and is an early adopter, and therefore has a higher network threshold than i2A, has also recently started using blogs. The conversations between these two colleagues, therefore, may have influenced i4A to consider using this

technology. Similarly, i2A uses online discussion forums and speaks directly with c1A, and also uses discussion forums. Since c1A is in the early majority of technology adoption and thus has a much lower network threshold than i2A, the conversation between these two instructors may have influenced c1A to use online discussion forums. However, since c1A also has conversations with the educational technologist in the department, t5A, this instructor may have heard about the online discussion forums from both t5A and i2A.

Department B

Figure 3 illustrates the social network for Department B and the betweenness centrality of the participants. In this figure, the large blue node, i5B, represents the instructor who has the highest betweenness centrality in the department since this instructor connects the left side of the network with the rest of the nodes. This instructor has conversations with i13B, who in turn has conversation with three other colleagues in the department who, based on the data available, do not have connections with anyone else in the department. Hence, i5B seems to play the intermediary role of helping information flow between the left and right sides of the network.

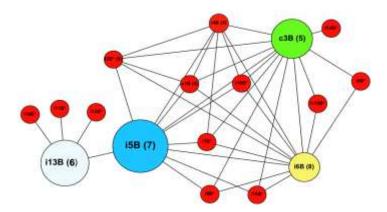


Figure 3: Partial social network of Department B

According to the interview and observation data, i5B is not only a high technology adopter in the department, but specifically uses digital media, technology that i13B also includes in teaching and learning. Furthermore, since i5B is an innovator and i13B falls within the early majority and hence, has a higher network threshold, the conversations between these two participants may have influenced i13B to explore digital media. Likewise, c3B and i6B also use digital media and a variety of other technologies that i5B has also adopted. Since instructors, c3B and i6B consider themselves to be early majority and early adopters respectively, their network thresholds are higher than that of i5B. Hence, conversations with i5B, and potentially with others, may have influenced their adoption of digital media. With respect to the correlation of technology adoption and betweenness centrality presented in Table 2, for the most part, participants in Department B, such as i5B, i13B, and c3B, who have adopted more technologies than others, also have greater betweenness centrality. Additionally, c3B is also a coordinator in the department, which may explain why this participant is more central than others who have adopted greater technology, such as i6B. However, i6B, represented by the yellow node at the far right of Figure 3, has adopted the most technology in the department, yet has lower betweenness centrality than i5B and i13B. This is due to i6B not being in an intermediary position to connect colleagues from one side of a network to another nor to facilitate the spread of information.

Department C

Figure 4, below, illustrates the betweenness centrality in Department C, which, as mentioned earlier, does not manifest the same trends as the other two departments. As illustrated in this Figure, the large blue node represents the participant with the largest betweenness centrality, c6C, who also has adopted less technology than others in the network (5 in total). The large white node represents the participant with the second highest betweenness centrality, c7C. However, unlike c6C, this participant has adopted the most technology in the department. These two participants are also the language coordinators in the department and therefore may have higher betweenness centrality than others, based on their responsibilities in the department. As noted earlier, the language coordinators in this department encourage the instructors to design and develop their own LMS environments. Therefore, their role in their department may explain their high betweenness centrality since they facilitate the spread of information across their department. However, the two green nodes represent the instructors with the next highest betweenness centrality scores, i10C and i11C, who do not have coordination responsibilities. One instructor, i10C, is a high technology adopter while the other, i11C, is a low technology adopter. Thus, a pattern of correlation between technology adoption and betweenness centrality does not emerge in this department.

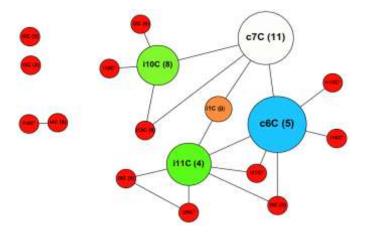


Figure 4: The partial social network of Department C

Investigating the types of technologies that the participants have chosen to adopt, however, shows that conversations amongst the participants may have had some influence on technology adoption. For instance, c7C is an early adopter and is a heavy user of PowerPoint Presentations and the online discussion board, which are both technologies that i10C and i12C also use. Since i10C is also an early adopter, the conversations between this instructor and c7C may have influenced both of them to use the technologies. The other instructor, i12C, is in the early majority group and, therefore, has a higher network threshold than the other two. Hence, conversations with i10C and c7C may have influenced i12C to consider using those technologies. In addition, i2C, represented by a small red node at the top of Figure 4, is also an early adopter and uses online discussions and digital media. This technology is also adopted by c7C. The intermediary position of i10C in the network, therefore, may facilitate the flow of information concerning online discussions and digital media between i2C and c7C. Likewise, i11C is in an intermediary position between i9C and i1C, who are the only participants who use the same vocabulary tool. Since i1C is an early adopter and i9C is in the early majority with a slightly higher network threshold, information about the vocabulary tool may have flowed from i1C to i9C through i11C.

Emerging Patterns

The analyses discussed earlier in this paper highlight two patterns. While departments A and B showed a positive correlation between technology adoption and betweenness centrality more than half of the time, a similarly significant relationship was not observed in Department C. However, analysis of the combined data such as with whom the participants spoke, which technologies they adopted and their network thresholds, showed that certain participants had an intermediary role, assisting with the flow of information across their departmental network and subsequently influencing their colleagues to consider certain technologies. This resonates with Burt's (1992) notion that structural holes create a gap in the flow of information between members of a network and a third person is needed to be an intermediary to fill this gap. Individuals near these bridges, therefore, have better opportunity to access new information that can lead to improving their social capital and influencing their decisions (Lin, 1999). Furthermore, there are parallels between this study and previous studies on collaboration and communication (Davis, 2005; Mwaura, 2003; Valente, 1996) in that there was also a trend in this study for conversations between those with lower network thresholds, such as the innovators, to have a potential influence on the technology adoption decisions of the participants with higher network thresholds, such as the early adopters or early majority. These findings also support the results of social network studies that have determined that communication amongst instructors can influence their decisions to use a particular teaching approach (Roxa & Martensson, 2009). The role of the participants with high betweenness centrality and the potential flow of information and technology adoption across the network also justify social network theory as a theoretical paradigm to explain technology adoption decisions.

The trend that emerged in two of the departments in this study begins to show that the technologically advanced instructors may also have positions of influence in their department networks since they tend to have an intermediary role that assists with the spread of information valuable to their colleagues and thus enhances overall social capital (Lin, 1999). It is likely that such spread of information and enhanced social capital is the result of key actors in the department networks developing trusting relationships with their colleagues (Niesz, 2007). This is of particular importance for senior higher education administrators and leaders since the success or failure of technology acceptance depends, to some extent, on their ability to identify the trail-blazing technology adopters who can help implement change and transform their institutions (Hagel et al., 2010). After these

adopters have been identified, the senior administration can enlist these key instructors to help promote the integration of educational technology by leading technology-related communities of practice (Kopcha, 2010; Roberts, 2008) or spreading information about new technologies through informal conversations with colleagues in their departments. One way for the senior administration to discover the influential instructors would be to identify the instructors who have adopted a high number of technologies as suggested by the trend revealed in this study. Since senior higher education administrators and leaders do not readily have access to information concerning which instructors at their institution have adopted the most technology, technology support units can play a critical role in obtaining such data and providing reports to senior administration. Information concerning the types and number of technologies that instructors use can be extracted from various technical systems, such as the learning management system, assisting educational institutions with implementing technology diffusion strategies (Dawson, McWilliam, & Tan, 2008). By leveraging the data supplied by the technology support units, senior higher education administrators can recruit the high technology-adopting instructors to help increase technology acceptance across their institution. Such technology diffusion strategies can assist educational institutions to better meet the demands of the global education market (Conole, 2010) by increasing access to online learning opportunities and enhancing student engagement. While this study discovered a potential correlation between network position and technology adoption, which can help identify key instructors to assist with technology diffusion, future studies, as discussed in the following section, are required to further determine its significance and applicability to the broader community.

Summary and Future Directions

This study investigated the social networks of academic departments and discovered a potential correlation between technology adoption and instructors' positions in their departmental networks. As reported, social network analysis of two departments showed that instructors who have adopted a greater number of technologies tend to be in an intermediary position in their department network and, hence, assist with the spreading of information across a departmental social network. Furthermore, this study revealed a tendency for instructors with greater betweenness centrality to have a lower network threshold than others, and therefore, the potential to influence adoption decisions of their colleagues demonstrating a higher network threshold. Both the instructors' particular intermediary role in their departmental network together with their ability to influence peers with higher network thresholds may be a result of the trust they have gained from others in their network. Future studies with a greater number and diversity of participants across disciplines are required to substantiate or refute the trends observed here. Further research can also help advance understanding of the factors influencing technology adoption amongst instructors, in particular the role that trust plays in certain instructors being in a position of influence in their professional social networks. In addition, since the social network analysis in this study was focused on ties between colleagues in academic departments, future studies can specifically investigate instructors' online social networks, such as Twitter and LinkedIn, to determine how they can be leveraged for enhancing technology adoption. Identification and recognition of factors influencing instructors' technology adoption decisions can assist with the provision of the resources and support necessary for higher education leaders to develop strategies for the integration of appropriate technologies within current teaching and learning practices. This study is merely a commencement point for discussion on the insights that social network analyses can bring forward, to aid and inform strategic initiatives designed to promote the use of learning technologies in the education context.

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Author contact details:

Negin Mirriahi: negin.mirriahi@ubc.ca, Shane Dawson: Shane.Dawson@unisa.edu.au, Debra Hoven: debrah@athabascau.ca

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