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Abstract. This paper presents results form an investigation of the relationship between student academic performance and social ties. Based on social capital and networked learning research, we hypothesized that i) students' social capital accumulated through their course progression is positively associated with their academic performance; and ii) students with more social capital have a significantly higher academic performance (operationalized as Grade Average Point score). Both hypotheses were supported by results of an empirical study that analyzed 10 years of student course enrolment records (N=505) in a master's degree program offered through distance education at a Canadian university. These results are consistent with previous studies which looked at social networks built through student interaction in classrooms or computer mediated communication environments. The significance of this research lies in the simplicity of the method used to establish student social networks from existing course

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registration records readily available through an institution’s student information system. A direct implication of this research is that i) study plans for students should consider investment in building new social ties in each course during degree programs; and ii) readily available data about cross-class networks can be used in software systems supporting study planning.

Introduction

Social interaction with peers has now, long been recognized as one of the critical factors for facilitating the learning process. The underlying principles of this work can be traced back to Vygotsky (1978) (1978) who noted that higher levels of internalization are reached through social interaction. As such educational research has developed numerous pedagogical approaches that are heavily based on social interaction (Bandura, 1977). This is especially true for contemporary pedagogies, which consider learners active constructors of their knowledge (Adams, 2006). Johnson & Johnson (2009) further support this concept noting that collaborative learning is one of the greatest success stories of education psychology. This was accomplished by establishing a relationship between theory, research, and practice. For example, it has been shown that social interaction leads to higher levels of cognition than individual learning (Schrire, 2006), while social interaction can also be beneficial for self-regulation of learning (Hadwin & Järvelä, 2011). Interactions in courses are also positively related to both academic performance and student satisfaction (Akyol & Garrison, 2011; Haythornthwaite, Kazmer, M.M., Robins, & Shoemaker, 2000; Johnson, Hornik, & Salas, 2008). The perceived diversity of educational benefits derived through social learning has resulted in a widespread adoption of socially interactive and collaborative pedagogies being adopted by practitioners (Dawson, 2008).

Implications of social interaction extend beyond pedagogical and educational psychology. College student retention research and practice (Tinto, 2006) posits that student retention is positively and strongly associated with social integration of students into the learning community (Thomas, 2000). Likewise, isolation and weak social presence are associated with dropout rates (Flood, 2002; Johnson, Hornik, & Salas, 2008). This may in part be explained by students tending to engage and interact with those with whom they share similar attitudes and values (Eckles & Stradley, 2012; Mayer & Puller, 2008). As such those who are strongly integrated are more likely to be motivated to remain within the network and hence have greater academic persistence (Bean, 1990). Therefore, efforts in research and practice in promoting student retention are seeking and offering alternative models of social integration, through informal activities (Hommes, et al., 2012) that strive to increase sense of belongingness to the community (Haythornthwaite, 2002) and mutual relatedness (Baumeister & Leary, 1995). The expectation is that such feelings of belongingness and relatedness might increase motivation to help each other (Stewart-Williams, 2007), and thus increase chances of retention (Thomas, 2000).

Methods of systematic analysis of social influences are essential. In this context, the study of social networks (social network analysis, SNA) in learning and education appears to be a very promising direction (Haythornthwaite, 2001; Haythornthwaite & de Laat, 2011; Haythornthwaite, in press). In this sense, the structural aspect of social networks is the primary analysis viewpoint. The structure of a social network consists of actors (i.e., nodes) and ties (i.e., edges) between them (Wasserman & Faust, 1994). The structure usually reflects paths of information diffusion across actors in the network structure (Burt, Kilduff, & Tasselli, 2013). SNA offers insights into both whole (i.e., collective) and actor (individual) social networks. Whole network analysis can indicate how well actors are connected (e.g., density) in networks; while, actor-level network analysis can detect popularity or centrality of nodes in networks (Wasserman & Faust, 1994).

Educational research is increasingly drawing on SNA methods, especially with the increasing opportunities for capturing social interactions through the use of computer-mediated communication (CMC) software (Wellman, et al., 1996). To date, the use of SNA in education has demonstrated that the structure of social networks is associated with sense of belonging (Haythornthwaite, 2001), sense of community (Dawson, 2008), creativity (Dawson, Tan, & McWilliam, 2011), effectiveness of student admission criteria (Dawson, Macfadyen, Lockyer, & Mazzochi-Jones, 2011), knowledge construction (de Laat, Lally, Lipponen, & Simons, 2007), academic persistence (Eckles & Stradley, 2012) and social integration (Thomas, 2000).

The association of academic performance and ties built in social networks has been in the foci of numerous studies. Scholars have been revisiting the traditional theory of academic performance (Meece, 2006), which posits that academic performance is predicted by academic ability and motivation by investigating different contextual factors (Rizzuto, LeDoux, & Hatala, 2009). Social ties, being an important contextual factor, have been shown to be positively associated with the academic performance in several studies (Baldwin, Bedell, & Johnson, 1997; Cho, Gay, Davidson, & Ingraffea, 2007; Hommes, et al., 2012; Mayer & Puller, 2008; Rizzuto, LeDoux, & Hatala, 2009; Smith & Peterson, 2007; Thomas, 2000; Yang & Tang, 2003; Yuan, Gay, & Hembrooke, 2006). Importantly, these studies have confirmed the positive association of social ties and academic performance in both classical classroom and CMC setting. However, these studies have typically used data collected from a single course where social ties and performance are limited to a single educational/learning situation (i.e., a single course). This single instance of learning is only one of many similar educational contexts that occur throughout a degree program.

This paper contributes to the existing body of knowledge by investigating the *association of academic performance and social ties, which students create through joint completion of courses while studying towards their university degrees*. In the rest of the paper, we will refer to such ties as *cross-class* social ties. Not only are cross-class social ties established through the concurrent enrolment of courses, but the record of such ties can easily be established from existing registration records that are generally readily available through the institution's student information system. Thus, the potential use of such data can directly be translated to academic institutions to better gauge academic standing of students in real-time in order to offer timely advice regarding learning support.

Theoretical Background and Hypotheses

Social Capital and Performance Benefits

Social capital is well-known as a theory that posits that social and economic benefits arise from social interactions (Granovetter, 2005). According to Putnam (1995), social capital is the "features of social organisation, such as networks, norms and trust that facilitate coordination and cooperation for mutual benefit" (p. 67). Similarly, Lin (2001) defined social capital as an "*investment in social relations with expected returns in the marketplace*" by focusing on the pragmatic aspects of social engagement. While Lin's definition relates to an identified 'return on investment' model through reference to the marketplace, this can be represented through numerous contexts such as economical, political, and significantly for this research *educational* (Dawson, 2008).

Not all types of social ties produce equal value and marketplace opportunities. In his seminal work, Granovetter (1973) distinguishes between strong and weak ties. Strong ties are usually associated with "friendship" networks or with ties that involve extensive interaction and well-established obligations, expectations, and trust. Weak ties are more associated with the notion of acquaintance or advice networks. Numerous studies indicated that advice networks are much more significant source of the reception of new ideas than friendship networks (Levin & Cross, 2004; Sparrowe, Liden, Wayne, & Kraimer, 2001). Moreover, performance indicators and personal gains are positively associated with weak ties and advice networks, such as Granovetter's classic example of finding a job (Levin & Cross, 2004; Nahapiet & Ghoshal, 1998; Sparrowe, Liden, Wayne, & Kraimer, 2001; Granovetter, The strength of weak ties, 1973).

Position in social networks is an important predictor of individual and group performance (Burt, 2005). As proposed by social resource theory (Lin, 1982), the socio-economic status of a person is related to their ability to access resources (e.g., information), which are available through their social relationships. Resources and information that are acquired can then be used to improve their own resources necessary to increase performance (Spreitzer, 1996). In this way, the embeddeness of an individual within a network can be seen to affect their ability to find the resources necessary to succeed. Therefore, the structure of social networks can used to estimate the amount of social capital to which an individual potentially has access (Lin, 1999; Seibert, Kraimer, & Liden, 2001). By making use of SNA, social capital is often gauged by using well-established centrality measures (Freeman, 1979) such as degree, betweenness and closeness (more details about these metrics are available in the Method section). Generally, two optimal network positions are most beneficial – central (e.g., degree) and brokerage positions (betweenness). People with high degree centrality have many social ties and are more active, recognized, important, and visible in their social networks (Brass, 1984). Thus, they are more likely to have higher access to social resources, which can enable them to enhance their performance (Sparrowe, Liden, Wayne, & Kraimer, 2001). On the other hand, the people with brokerage positions are in control over *different (i.e., non-redundant)* social resources available in several sub-groups. Burt (2005) describes network brokers as persons who bridge *structural holes* in a network. In essence, these individuals are in a network position to be exposed to many non-redundant social resources, which allow them to control information flow, and potentially to produce more innovative results (Burt, 2004). Consequently, empirical research of social capital reports that centrality and brokerage positions are positively associated with benefits such as promotion (Burt, 2005), power (Brass, 1984), innovation (Ibarra, 1993; Tortoriello & Krackhardt, 2010; Burt, 2004), and creativity (Sosa, 2012).

Social Capital and Academic Performance

Given the importance of social ties on performance recognized in social capital research and due to the growing attention to social learning, educational research has also started investigating the impact of social ties on academic performance. Traditionally, prediction of future academic performance is based on an individual's academic ability and motivation where typically past performance is a surrogate for ability (Meece, 2006; Yorke, 1991). Much less is however known about the impact of contextual factors (e.g., social ties, use of technology, or class size) on academic performance (Rizzuto, LeDoux, & Hatala, 2009).

There have been several research studies that have investigated the impact of social ties and structural network position on academic performance. Baldwin et al. (1997) examined the association of social ties and academic performance in an undergraduate course of a Master's of Business Administration program. Using self-reports to collect information about social ties, Baldwin et al. extracted three types of social networks – friendship, communication (also referred to as advice in related work (Smith & Peterson, 2007)) and adversarial. Consistent with the importance of weak ties (Granovetter, The strength of weak ties, 1973) and network centrality (Sparrowe, Liden, Wayne, & Kraimer, 2001) for socio-economic benefits, Baldwin et al. observed that (degree) centrality in advice networks had a significant positive effect on academic performance. They also found that friendship ties (positively) and adversarial ties (negatively) were associated with satisfaction, but had no association with performance. These results have also been confirmed in a study conducted in a management information systems course (Yang & Tang, 2003).

The importance of centrality for academic performance has also been shown in several other studies. For example, Smith & Peterson (2007) found that “prestige” (i.e., in-degree centrality) in advice networks was positively associated with academic performance in a communication undergraduate class; contrary to advice networks, “prestige” in friendship networks was negatively associated with the performance. Likewise, (degree and closeness) centrality in emergent (communication) networks established in an engineering class (Cho, Gay, Davidson, & Ingraffea, 2007) was positively associated with performance, unlike position in pre-existing (friendship) networks, which had no significant association with performance. In a study with students in a medical course, Hommes et al. (Hommes, et al., 2012) identified that (degree) centrality in friendship networks was positively associated with academic performance, but had a much lower effect than centrality (both in- and out-degree) in advice networks. Similar to the study of Hommes et al., Thomas (2000) also found a positive association of (out-degree) centrality in a combined friendship and communication network and academic performance. Unlike other studies, Thomas collected data from an entire freshmen year student population in a liberal arts college and academic peformance was operationalized by Grade Point Average (GPA) values of the study participants.

In addition to centrality positions, effects of other network positions has also been investigated on academic peformance. Rizzuto et al. (2009) found that density of students' actor networks was positively associated with academic performance in an introductory psychology first-year college class. This result is more consistent with the traditional perspective of the importance of social capital in high-school student-and-parent networks (Coleman, 1988), where network closure is used as a measure of social capital.

Cross-class Networks and Academic Performance

While the numerous studies investigating the association of social networks and academic performance have demonstrated clear correlations, these studies have been isolated to a single course. Only Thomas' study (2000) considered the impact of social networks of an entire freshmen class on students' GPA through an observational study with data collection in the beginning and the end of an academic year. However, Thomas did not consider the impact of the individual courses that students had taken during their first academic year. It seems reasonable to assume that social networks of college students are built through their enrollment in multiple individual courses while studying towards their academic degrees. As such there is capacity to accumulate social capital across and within each course. Thus, there is a need to study the impact of cross-course social capital on overall student performance.

The importance for social interaction and identifying social capital is further stressed when referencing online and distance education degree programs. As noted by (Dawson, 2008), social capital is predominantly established through online social interactions. Being part of the same temporal group created by their course enrollment increases chances for social interaction between students due to the human need to belong to a group (Baumeister & Leary, 1995). Moreover, students gain shared experience and theoretically create a 'latent tie' structure on which ties can be built (e.g., seeing the same students in two-three different classes, one becomes familiar with faces and common subjects to talk about (Haythornthwaite, 2002). As ego networks of students enrolled in the same course will likely overlap, mutual trust among the students is likely less risky (Coleman, 1988) allowing them to increase network closure (i.e., to build more dense network). While just being enrolled in the same course at the same time does not necessarily mean building strong ties, it still provides some ground for establishing weak ties, which can be used for communication of information (i.e., building communication/advice networks). Therefore, we hypothesize that

Hypothesis 1: *Students' social capital accumulated through their enrollment in courses while pursuing a degree program is positively associated with their academic performance.*

Given the presented evidence about the positive association of network position with academic performance as well as more grater socio-economic benefits in general sense (Burt, Kilduff, & Tasselli, 2013), and as a direct consequence of Hypothesis 1, it seems reasonable to hypothesize that

Hypothesis 2: *Students with more social capital in cross-class networks have a significantly higher academic performance*.

This stems from the notion that students with a higher number of information sources are less dependent on single sources of information in their networks (Cook & Emerson, 1978) and therefore possess easier modes of access to important resources of relevance for their studies. Moreover, according to (Baldwin, Bedell, & Johnson, 1997), students with more extensive cross-class networks are likely to have access to a broader range of views, which can result in a larger quantity and better quality of information.

Method

Sample

Accepting the data collection method reported by Eckles & Stradley (2012), archival data from course registration records of a master's in information systems program in an online Canadian university was used for analysis in this study. Moreover, the use of trace data to establish social networks from discussions in CMC software is an established practice in education research (Bakharia & Dawson, 2011; Dawson, Macfadyen, Lockyer, & Mazzochi-Jones, 2011; Garton, Haythornthwaite, & Wellman, 1997).The program has the typical requirements necessary for completion of a master's degree in computing/information systems in the North American educational systems. The program is completely delivered through an online, distance education model with courses enrolling up to 30-40 students per session. Course content and group learning is delivered by using the learning management system Moodle. The program has two student intakes per year and typically caters to part-time students who usually maintain their regular employment. Enrolled students are not requested to follow any predefined course registration, i.e., the program does not follow a cohort-based learning model (although, course prerequisites exist and drive the sequence of course completion). The sample included 10 years of archival data about course registration since the program inception in 2001 until January 2011. The archival data contained information about course registration, course grades, course extensions, and course withdrawals of each student enrolled in the program. From the original sample, we excluded all those who did not collect any credits (students who were either recently enrolled in the program or were inactive), since we could not calculate their academic performance (i.e., GPA). The remaining sample (N=505) was used to extract the variables for our analysis.

Data Collection and Social Networks

Social networks were derived by following a similar method as described in (Eckles & Stradley, 2012). We created a link between all students who had been enrolled into the same section of a course. Such data allowed us to create undirected social graphs. A weight of the link between two students was determined by the number of course they had taken together (e.g., if they took three courses, their link would have weight three). In the case of a course withdrawal, the link between a student who withdrew and the rest of the group was considered weaker by dividing the number of days the student persisted in the course with the total scheduled course duration (days). In case of a course extension[†], the link between a student who had taken an extension and the rest of the group was weighted by dividing the regular number of days the course lasted for with the overall number of days the student stayed in the course (i.e., the regular time of the course plus the extension time).

Variables and Measurement

To assess the student social capital we used standard methods adopted (Borgatti, Jones, & Everett, 1998) in previous studies investigating the association between social capital and academic performance. As already discussed, measures of centrality are typically used as a way to gauge an individual's social capital. In particular, in our study, we calculated the following measures of centrality, (Brandes, 2001; Freeman, 1979; Hage & Harary, 1995) of each study participant:

- Degree centrality – the number of social ties a node has in a social network;
- Closeness centrality – the distance of a node to all other nodes in a social network;

[†] In some courses, students are allowed to take up to two two-month long course extensions.

- Betweenness centrality – the number of shortest paths between any two nodes that go through a given node;
- Eccentricity – the distance between a node and its farthest node in a social network.

All the above social networking variables were computed by using the Gephi open source software for social network analysis (Bastian, Heymann, & Jacomy, 2009).

For each student we also constructed variables representing: GPA, the number of days they spent in the program (by summing the days they spent in the individual courses), the number of course credits they had collected until our data collection (January 2011), the number of course extensions, and the number of course withdrawals. The program follows a standard North-American system where a typical course is worth three credits.

Analysis

Distribution of variables was explored for normality by using the Kolmogorov-Smirnov and Shapiro-Walk tests. This was further explored by using P-P plots. Non-normally distributed variables were transformed using natural logarithm for statistical analysis (Keene, 1995). Given the non-normal distribution of variables, characteristics of the participants were presented as median (25^{th} and 75^{th} percentile) (Table 1).

To test Hypothesis 1, we used linear regression, given that our outcome variable was GPA (i.e., continuous variable). We performed four regression analyses, one for each centrality measure as an independent variable. The regression models were adjusted for confounding variables affecting the investigated association including: the number of days they spent in the program; the number of course credits; the number of course extensions; and the number of course withdrawals. Beta (B), standard error (SE) and standardized β coefficients for the independent variables and the adjusted R^2 values are reported for all four regression models.

To test Hypothesis 2, we first split our sample into groups based on students' amount of social capital, which was operationalized by centrality measures that were significantly associated with GPA. Mean values of GPAs between these groups were compared using General Linear Model adjusted for the number of days they spent in the program, the number of course credits, the number of course extensions and the number of course withdrawals. The Bonferroni post-hoc test was used for pair-wise comparison between the groups.

Results are considered significant if $p < .05$. All statistical tests were performed using the statistical package for social sciences SPSS v19.

Results

The descriptive statistics of each variable used in our study are shown in Table 1. Given our data collection method (extraction from institutional archival data), we had no missing data. Thus, no strategy for treating data was needed. We used these data to test our two hypotheses.

Table 1. Characteristics of the study participants (N=505)

Hypothesis 1

To test if there is a positive association between the students' academic performance (operationalized as GPA) and students' social capital in cross-class networks, operationalized as four separate actor level centrality measures, we performed four regression analyses, one for each centrality measure. Table 2 shows the results of the regression analyses. No significant association was found between actor degree and betweenness centralities and GPA. However, the results show significant associations between closeness centrality and GPA and eccentricity and GPA. These associations persist over and above the four confounding variables (i.e., the number of course credits, the number of days spent in the program, the number of course withdrawals and the number of course extensions). Namely, these associations hold at any level of the confounding variables. In these adjusted models, for each one percent increase in closeness centrality, we found an average of about 0.7% decrease in GPA ($B \pm SE = -.68 \pm .15$). Likewise, one percent increase in eccentricity was found to be associated with about 0.8% decrease in GPA ($B \pm SE = -.68 \pm .15$). Based on these results, we can accept hypothesis 1 (the further rationale for accepting Hypothesis 1 is given in the Discussion section).

Table 2. Results of regression analysis testing the association between the students’ GPA and centrality measures (social capital independent variables). All the regression models are adjusted for the confounding variables shown in Table 1

Hypothesis 2

To test if students with more social capital in cross-class networks have significantly higher performance (Hypothesis 2), we first needed to divide the participants into groups based on the amount of their social capital. The two measures of social capital shown to be significantly associated with the GPA variable (i.e. closeness centrality and eccentricity) were used as the criteria for creating the groups. In case of closeness centrality, we divided participants in quartiles Q1–Q4 whereby Q1 is the top quartile (i.e., highest social capital) and Q4 is the bottom quartile (i.e. lowest social capital). As shown in Table 3, General Linear Model revealed significant differences between the four groups. The Bonferroni post-hoc test showed that both the Q1 and Q2 groups had significantly higher GPA values than the Q3 and Q4 groups. While no significant difference was revealed between Q1 and Q2 in the level of GPA, the geometric mean values of GPA in Table 3 indicate higher values of GPA in the Q1 group than in the Q2 group. Given that the General Linear Model was adjusted for the four confounding variables, we can conclude that the differences between the groups persists over and above the number of course credits, the number of days spent in the program, the number of course withdrawals and the number of course extensions. Namely, these differences hold at any level of the confounding variables.

Table 3. GPA across quartiles of closeness

In case of eccentricity, it was not possible to divide the participants into four groups. Eccentricity is an integer value assigned to each node representing the distance to the farthest node. The social network constructed from our sample, resulted in eccentricity values ranging from 3–6; with 33 participants with eccentricity value of 3 and only three participants with eccentricity value of 6. Given the small size of these groups, there was insufficient statistical power to determine the differences between the groups. To address this issue we divided our participants into two groups – higher social capital (eccentricity values 3 and 4) and lower social capital (eccentricity 5 and 6). As illustrated in Table 4, there was a statistically significant difference between the two groups whereby the higher social capital group (lower eccentricity score) had significantly higher values of GPA than the lower social capital group. This difference persists over and above the confounding variables – the number of course credits, the number of days spent in the program, the number of course withdrawals, and the number of course extensions. That is, the difference holds hold at any level of the confounding variables.

Table 4. Differences in GPA between the higher and lower social capital groups based on eccentricity

Based on the results reported, we can accept our hypothesis 2 stating that students with higher levels of social capital have significantly higher GPA values than those with lower levels of social capital in cross-class social networks.

Discussion and Conclusions

Measurement of Social Capital in Cross-Class Networks

When considering the results reported on the association between social capital and GPA values, the negative values of unstandardized B and standardized β coefficients might look surprising and could mislead researchers to the conclusion that the association between social capital and GPA i negative. However, such negative values for the coefficients were expected (Borgatti, Jones, & Everett, 1998) and consistent with the definitions of the given measures of social capital – closeness (Freeman, 1979) and eccentricity (Hage & Harary, 1995). Namely, these two measures should be interpreted as follows – the lower the values of eccentricity/closeness centrality the higher the amount of social capital. That is, those with lower values of eccentricity have a shorter distance to any node in the network, and those with lower values of closeness centrality have a shorter distance to all nodes in the network. Thus, the association between social capital and GPA is positive. This finding has further implications.

The significant association of GPA with eccentricity and closeness centrality suggests that the value of social capital gained through cross-class networks stems from the capacity for an individual to target and access pertinent information that is often diffused throughout the network. This interpretation relates to prior research on the importance of distances to access information through social networks while looking for job opportunities (Granovetter, 1973; Granovetter, 2005). Similarly, our results indicate that with the increase in the distance (expressed both as closeness and eccentricity) with other nodes in cross-class networks results in a decrease in the GPA of the student.

Limitations

It is important to indicate that our hypotheses were confirmed by the results that are tested in a specific context. Namely, our study sample was from a master’s degree program fully offered through online distance education without predefined cohorts. Moreover, due to a social constructivist component integrated into the program design, the courses are not larger than 30-40 students (Anderson & Dron, 2011). To further validate our findings, it is necessary to organize studies in different contexts in order to be able to estimate conditions under which hypotheses are valid, and which conditions might change our findings.

Our study did not investigate how and if cross-class networks are associated with the variables that are traditionally used as predictors of academic performance – ability and motivation (Robbins, et al., 2004). As academic performance has been shown as a solid proxy of academic ability (Senko, Hulleman, & Harackiewicz, 2011), it seems important to investigate the relation between the progression of the social capital development and GPA accumulation for each individual course students take in a degree program.

We have already stated that our study did not investigate the impact of external networks. While this can be improved by taking into account networks students built through online discussions inside courses or informal social networking software, it still seem necessary to collect data from students by asking them to self-report different types of social networks they perceive as important for their academic performance. For example, as Dawson (2008) showed, for some students the primary source of social capital could be the networks, which are not directly related to their academic institution and degree program (e.g., coworkers or family members). Therefore, it is important to investigate the impact of such external networks on cross-class networks when predicting academic performance.

Implication for Educational Research and Practice

An important implication of our study is that cross-class networks can serve as a promising basis for estimating students’ academic performance. In fact, the results of our research are consistent with related work which had also investigated association of social networks and academic performance (Cho, Gay, Davidson, & Ingraffea, 2007; Hommes, et al., 2012; Mayer & Puller, 2008; Rizzuto, LeDoux, & Hatala, 2009; Smith & Peterson, 2007; Thomas, 2000; Yang & Tang, 2003; Yuan, Gay, & Hembrooke, 2006; Baldwin, Bedell, & Johnson, 1997). However, these previous studies only considered academic performance at the level of a single course and constructed social networks by using questionnaires asking students to self-report their friends and acquaintances in the studied courses. Thus, there are two importance implications of our research. *First*, longer-term measures of academic performance (i.e., GPA) can be gauged based on students’ social capital accumulated in cross-class networks. This is especially significant, as our results persist over and above the four key confounding variables – the number of days spent in the academic program, the number of credits, the number of course extensions, and the number of course withdrawals. That is, academic performance is associated with social capital for all values (e.g., any number of days spent in the program) of the confounding variables. As such, cross-class networks can serve as a promising basis for sources of early estimation of student success in academic degree programs. *Second*, our method for data collection can easily be applied to any academic institution to construct cross-class networks from course registration records. Not only is this significant in terms of the opportunity to readily replicate the current study, but also it eliminates a critical limitation of data collection methods commonly prompted in the studies that relied on the surveys gathering self-reported social networks. In fact, recently, a similar method for social network extraction was used in (Eckles & Stradley, 2012) to investigate if student persistence to retain in an academic program was based on social capital. We hope that future research will further investigate suitability of this network extraction method in different contexts to test validity of our findings.

The higher number of social ties does not guarantee a better academic performance, as shown in the results testing association between degree centrality and the academic performance (i.e., GPA). First, our study has not shown any causality between the social capital in cross-class networks; it have only revealed associational aspect between academic performance and social capital. Second, this result might appear at surface as contradictory to other studies who typically found a significant association between degree centrality and academic performance (Baldwin, Bedell, & Johnson, 1997; Hommes, et al., 2012; Smith & Peterson, 2007; Yang & Tang, 2003), all of which investigate the association at the level of a single course and in an on-campus setting; these studies did also not report if they tested the association between other centrality measures and academic performance at all. However, studies that did test the association between other centrality measures (e.g., betweenness and closeness) at both course (Cho, Gay, Davidson, & Ingraffea, 2007) and an academic year (Thomas, 2000) levels had consistent results with ours. Moreover, the lack of association between degree centrality and academic performance was expected, given the way we theorized cross-class networks (in the Theoretical

Background and Hypotheses section) to be based on weak ties established through joint participation in the same course offering. Indeed, prior research in both work and educational environments has shown that actor-level networks with too many weak ties can lead to a decrease in performance (Cross & Thomas, 2008; Hommes, et al., 2012). The results in this current study show that students need to be able to build their social capital by building their opportunities to easily access information from other students in the program. This also has another direct implication of both research and practice.

Building social capital through cross-class networks does not mean always registering with all new students in a next course. On the contrary, we hypothesize that ideally course registration should balance these three aspects: i) access to the students who are longer in the program (i.e., to facilitate accessing those who are advanced in the completion of a degree program's requirements); ii) access to the students who are shorter in the program (i.e. facilitate accessing to those who have recently joined the degree program); iii) strengthening ties with those with whom some previous courses were taken (to facilitates building of trust and feeling of relatedness as well as ease the start of communication in early stages of new courses (Haythornthwaite, 2002; Rizzuto, LeDoux, & Hatala, 2009; Stewart-Williams, 2007).

It seems appealing to recommend to institutions to advise their students who they will be taking their courses with in order to build their social capital. This is reasonable to suggest based on the pragmatism behind social network development (Townsend & Wilson, 2009) and social exchange theory**,** which posits that personal interest drives people to look for social relationships (Molm & Cook, 1995)**.** In fact, according to Nahapiet & Ghoshal (1998), the extent to which an individual invests in new social and intellectual capitals has a significant impact on the individual's performance. It seems reasonable to expect that students' performance will be increased if they are trained about how to build and maintain their social capital, as already shown with positive performance implications of a similar training offered to executives (Burt & Ronchi, 2007). This is the logic behind the concept of *learning communities* in universities (Gabelnick, MacGregor, Matthews, & Smith, 1990), where for example members of particular residences get their first year courses together. In an online, distance education program, this concept could be hard to implement, given the specific needs for the student populations who are typically part-time students and who typically have higher need for flexibility than programs in on-campus environments.

Of course, such a pragmatic perspective to cross-class networks may not be viewed favorably by students (Villara & Albertína, 2010) if it is not sensitively introduced and pedagogically justified. Clearly, as shown in the workplace setting, the importance of social capital is essential for a successful career (Burt & Ronchi, 2007). Students should be offered with educational opportunities that will help them learn to appreciate the importance of being exposed to diverse perspectives while studying towards their degrees (Burt, 2004). Not only could students be advised with whom to take their courses, but the students could also be provided with additional opportunities to informally build and strengthen their social ties (Hommes, et al., 2012) as well as through social learning activities in existing courses. For fully distance education degree programs, using online social networking software is a promising opportunity; for on-campus programs, such online networks can complement already existing extracurricular activities students can be involved in (Eckles & Stradley, 2012). A natural future research direction is to investigate the relationships between social ties built in cross-course networks with networks build through social interactions in courses (e.g., online discussions

(Bakharia & Dawson, 2011; Harrer, Zeini, & Pinkwart, 2005; Reffay & Chanier, 2003)) and informal communication channels.

References

Adams, P. (2006). Exploring Social Constructivism: Theories and Practicalities. *Education, 34*(3), 243-257. doi:10.1080/03004270600898893

Akyol, Z., & Garrison, D. R. (2011). Understanding Cognitive Presence in an Online and Blended Community of Inquiry: Assessing Outcomes and Processes for Deep Approaches to Learning. *British Journal of Educational Technology, 42*(2), 233-250. doi:10.1111/j.1467-8535.2009.01029.x

Anderson, T., & Dron, J. (2011). Three generations of distance education pedagogy. *The International Review of Research in Open and Distance Learning, 12*(3), 80-97.

Bakharia, A., & Dawson, S. (2011). SNAPP: a bird's-eye view of temporal participant interaction. *Proceedings of the 1st International Conference on Learning Analytics and Knowledge* (pp. 168-173). Banff, AB, Canada: ACM Press. doi:10.1145/2090116.2090144

Baldwin, T. T., Bedell, D. M., & Johnson, J. L. (1997). The social fabric of a team-based M.B.A.program: Network effects on student satisfaction and performance. *Academy of Management Journal, 40*(6), 1369-1397. doi:10.2307/257037

Bandura, A. (1977). *Social Learning Theory.* General Learning Press.

Bastian, M., Heymann, S., & Jacomy, M. (2009). Gephi: An open source software for exploring and manipulating networks. *Proceedings of the 3rd International AAAI Conference on Weblogs and Social Media* (pp. 361-362). San Jose: AAAI Press.

Baumeister, R. F., & Leary, M. R. (1995). The need to belong: Desire for interpersonal attachments as a fundamental human motivation. *American psychological association, 117*(3), 497–529. doi:10.1037/0033-2909.117.3.497

Bean, J. P. (1990). Why Students Leave: Insights from Research. In D. Hossler, & J. P. Bean, *Enrollments, The Strategic Management of College.* San Francisco: Jossey-Bass Inc.

Borgatti, S. P., Jones, C., & Everett, M. G. (1998). Network Measures of Social Capital. *Connections, 21*(2), 27-36.

Brandes, U. (2001). A Faster Algorithm for Betweenness Centrality. *Journal of Mathematical Sociology, 25*(2), 163-177. doi:10.1080/0022250X.2001.9990249

Brass, D. J. (1984). Being in the right place: A structural analysis of individual influence in an organization. *Administrative Science Quarterly, 29*(4), 518–539. doi:10.2307/2392937

Burt, R. S. (2004). Structural Holes and Good Ideas. *American Journal of Sociology, 110*(2), 349–399. doi:10.1086/421787

Burt, R. S. (2005). The Social Capital of Structural Holes. In M. F. Guillen, R. Collin, P. England, & M. Meyer, *The New Economic Sociology* (pp. 148–192). New York: Russell Sage Foundation. Retrieved from http://faculty.chicagobooth.edu/ronald.burt/research/files/SCSH.pdf

Burt, R. S., & Ronchi, D. (2007). Teaching Executives to See Social Capital: Results from a Field Experiment. *Social Science Research, 36*(3), 1156-1183. doi:10.1016/j.ssresearch.2006.09.005

Burt, R. S., Kilduff, M., & Tasselli, S. (2013). Social Network Analysis: Foundations and Frontiers on Advantage. *Annual Review of Psychology, 64*, in press. doi:10.1146/annurev-psych-113011-143828

Cho, H., Gay, G., Davidson, B., & Ingraffea, A. (2007). Social networks, communication styles, and learning performance in a CSCL community. *Computers & Education, 49*(2), 309–329. doi:10.1016/j.compedu.2005.07.003

Coleman, J. S. (1988). Social Capital in the Creation of Human Capital. *The American Journal of Sociology, Vol. 94, Supplement*, S95-S120.

Cook, K. S., & Emerson, R. M. (1978). Power, equity and commitment in exchange networks. *American Sociological Review, 43*(5), 721-739. doi:10.2307/2094546

Cross, R., & Thomas, R. J. (2008). How Top Talent Uses Networks and Where Rising Stars Get Trapped. *Organizational Dynamics, 37*(2), 165–180.

Dawson, S. (2008). A study of the relationship between student social networks and sense of community. *Educational Technology & Society, 11*(3), 224–238.

Dawson, S., Macfadyen, L., Lockyer, L., & Mazzochi-Jones, D. (2011). Using social network metrics to assess the effectiveness of broad based admission practices. *Australasian Journal of Educational Technology, 27*(1), 16-27.

Dawson, S., Tan, J. P., & McWilliam, E. (2011). Measuring creative potential: Using social network analysis to monitor a learners' creative capacity. *Australasian Journal of Educational Technolog, 27*(6), 924-942.

de Laat, M., Lally, V., Lipponen, L., & Simons, R.-J. (2007). Investigating patterns of interaction in networked learning and computer-supported collaborative learning: A role for Social

Network Analysis. *International Journal of Computer-Supported Collaborative Learning, 2*(1), 87-103. doi:10.1007/s11412-007-9006-4

Eckles, J. E., & Stradley, E. G. (2012). A social network analysis of student retention using archival data. *Social Psychology of Education, 15*(2), 165-180. doi:10.1007/s11218-011-9173-z

Flood, J. (2002). Read All About It: Online Learning Facing 80% Attrition Rate. *Turkish Online Journal of Distance Education, 3*(2).

Freeman, L. (1979). Centrality in social networks - Conceptual clarification. *Social Networks, 1*(3), 215-239. doi:10.1016/0378-8733(78)90021-7

Gabelnick, F., MacGregor, J., Matthews, R. S., & Smith, B. L. (1990). *Learning Communities: Creating Connections Among Students, Faculty, and Disciplines. New Directions for Teaching and Learning* (Vol. 40). San Francisco, CA: Jossey-Bass.

Garton, L., Haythornthwaite, C., & Wellman, B. (1997). Studying Online Social Networks. *Journal of Computer-Mediated Communication, 3*(1). doi:10.1111/j.1083-6101.1997.tb00062.x

Granovetter, M. (1973). The strength of weak ties. *American Journal of Sociology, 78*(6), 1360-1380. Retrieved from http://www.jstor.org/stable/2776392

Granovetter, M. (2005). The Impact of Social Structure on Economic Outcomes. *The Journal of Economic Perspectives, 19*(1), 33-50. doi:10.1257/0895330053147958

Hadwin, A., & Järvelä, S. (2011). Introduction to a special issue on social aspects of self-regulated learning: Where social and self meet in the strategic regulation of learning. *Teachers College Record, 113*(2), 235-239.

Hage, P., & Harary, F. (1995). Eccentricity and centrality in networks. *Social Networks, 17*(1), 57-63. doi:10.1016/0378-8733(94)00248-9

Harrer, A., Zeini, S., & Pinkwart, N. (2005). The effects of electronic communication support on presence learning scenarios. *In Proceedings of th 6th conference on Computer support for collaborative learning*, (pp. 190-194). Taipei, Taiwan.

Haythornthwaite, C. (2001). Exploring multiplexity: Social network structures in a computer-supported distance learning class. *The Information Society, 17*(3), 211-226. doi:10.1080/01972240152493065

Haythornthwaite, C. (2002). Building social networks via computer networks: Creating and sustaining distributed learning communities. In K. A. Renninger, & W. Shumar, *Building virtual communities: Learning and changein cyberspace* (pp. 159-190). New York: Cambridge University Press.

Haythornthwaite, C. (2002). Strong, Weak, and Latent Ties and the Impact of New Media. *The Information Society, 18*(5), 385-401. doi:10.1080/01972240290108195

Haythornthwaite, C. (in press). Learning networks. In R. Alhajj, *Encyclopedia of Social Networks and Data Mining.* Springer.

Haythornthwaite, C., & de Laat, M. (2011). Social network informed design for learning with educational technology. In A. Olofsson, & J. O. Lindberg, *Informed Design of Educational Technologies in Higher Education: Enhanced Learning and Teaching* (pp. 352-374). Hershey, PA: IGI Global.

Haythornthwaite, C., Kazmer, M.M., Robins, J., & Shoemaker, S. (2000). Community development among distance learners: Temporal and technological dimensions. *Journal* *of Computer-Mediated Communication, 6*(1). Retrieved from http://jcmc.indiana.edu/vol6/issue1/haythornthwaite.html

Hommes, J., Rienties, B., Grave, W. d., Bos, G., Schuwirth, L., & Scherpbier, A. (2012). Visualising the invisible: a network approach to reveal the informal social side of student learning. *Advances in Health Education, 17*(5), 743-757. doi:10.1007/s10459-012-9349-0

Ibarra, H. (1993). Network centrality, power and innovation involvement: determinants of technical and administrative roles. *Academy of Management Journal, 36*(3), 471-501. doi:10.2307/256589

Johnson, D. W., & Johnson, R. T. (2009). An Educational Psychology Success Story: Social Interdependence Theory and Cooperative Learning. *Educational Researcher, 38*(5), 365-379. doi:10.3102/0013189X09339057

Johnson, R. D., Hornik, S., & Salas, E. (2008). An empirical examination of factors contributing to the creation of successful e-learning environments. *International Journal of Human-Compututer Studies, 66*(5), 356-369. doi:10.1016/j.ijhcs.2007.11.003

Keene, O. (1995). The Log-Transformation is Special. *Statistics in Medicine, 14*(8), 811-819. doi:10.1002/sim.4780140810

Levin, D. Z., & Cross, R. (2004). The strength of weak ties you can trust: The mediating role of trustin effective knowledge transfer. *Management Science, 50*(11), 1477-1490. doi:10.1287/mnsc.1030.0136

Lin, N. (1982). Social resources and instrumental action. In P. V. Marsden, & N. Lin, *Social structure and network analysis* (pp. 131–145). London: Sage.

Lin, N. (1999). Building a Network Theory of Social Capital. *Connections, 22*(1), 28-51.

Lin, N. (2001). *Social capital: A theory of social structure and action.* Cambridge: Cambridge University Press.

Mayer, A., & Puller, S. L. (2008). The Old Boy (and Girl) Network: Social Network Formation on University Campuses. *Journal of Public Economics, 92*(1-2), 329–347. doi:10.1016/j.jpubeco.2007.09.001

Meece, J. L. (2006). Classroom Goal Structure, Student Motivation, and Academic Achievement . *Annual Review of Psychology, 57*, 487-503. doi:10.1146/annurev.psych.56.091103.070

Molm, L. D., & Cook, K. S. (1995). Social exchange and exchange networks. In K. S. Cook, G. A.Fine, & J. S. House, *Sociological perspectives on social psychology* (pp. 209-235). Needham Heights, MA: Allyn & Bacon.

Nahapiet, J., & Ghoshal, S. (1998). Social capital, intellectual capital, and the organizational advantage. *Academy of Management Review, 23*(2), 242–266. doi:10.2307/259373

Putnam, R. (1995). Bowling Alone: America's Declining Social Capital. *Journal of Democracy, 6*(1), 64–78. doi:10.1353/jod.1995.0002

Reffay, C., & Chanier, T. (2003). How social network analysis can help to measure cohesion in collaborative distance-learning. *In Proceedings of the 6th International Conference on Computer Supported Collaborative Learning* , (pp. 343-352). Bergen.

Rizzuto, T. E., LeDoux, J., & Hatala, J. P. (2009). It's not just what you know, it's who you know: Testing a model of the relative importance of social networks to academic performance. *Social Psychology of Education, 12*(2), 175-189. doi:10.1007/s11218-008-9080-0

Robbins, S. B., Lauver, K., Le, H., Davis, D., Langley, R., & Carlstrom, A. (2004). Do Psychosocial and Study Skill Factors Predict College Outcomes? A Meta-Analysis. *Psychological Bulletin, 130*(2), 261-288. doi:10.1037/0033-2909.1

Schrire, S. (2006). Knowledge building in asynchronous discussion groups: Going beyond quantitative analysis. *Computers & Education, 46*(1), 49-70. doi:j.compedu.2005.04.006

Seibert, S. E., Kraimer, M. L., & Liden, R. C. (2001). A Social Capital Theory of Career Success. *The Academy of Management Journal, 44*(2), 219-237. doi:10.2307/3069452

Senko, C., Hulleman, C. S., & Harackiewicz, J. M. (2011). Achievement Goal Theory at the Crossroads: Old Controversies, Current Challenges, and New Directions. *Educational Psychologist, 46*(1), 26-47. doi:10.1080/00461520.2011.538646

Smith, R. A., & Peterson, B. L. (2007). “Psst … What Do You Think?” The Relationship between Advice Prestige, Type of Advice, and Academic Performance. *Communication Education, 56*(3), 278-291. doi:10.1080/03634520701364890

Sosa, M. E. (2012). Where Do Creative Interactions Come From? The Role of Tie Content and Social Networks. *Organization Science*, in press. doi:10.1287/orsc.1090.0519

Sparrowe, R. T., Liden, R. C., Wayne, S. J., & Kraimer, M. L. (2001). Social Networks and the Performance of Individuals and Groups. *The Academy of Management Journal, 44*(2), 316-325. doi:10.2307/3069458

Spreitzer, G. M. (1996). Social structural characteristics of psychological empowerment. *Academy o fManagement Journal, 39*(2), 483–504. doi:10.2307/256789

Stewart-Williams, S. (2007). Altruism among kin vs. nonkin: Effects of cost of help and reciprocal exchange. *Evolution and human behavior, 28*(3), 193–198. doi:10.1016/j.evolhumbehav.2007.01.002

Thomas, S. L. (2000). Ties That Bind: A Social Network Approach to Understanding Student Integration and Persistence. *The Journal of Higher Education, 71*(5), 591-615. doi:10.2307/2649261

Tinto, V. (2006). Research and Practice of Student Retention: What Next? *Journal of College Student Retention: Research, Theory and Practice, 8*(1), 1-19. doi:10.2190/4YNU-4TMB-22DJ-AN4W

Tortoriello, M., & Krackhardt, D. (2010). Activating cross-boundary knowledge: The role of Simmelian Ties in the generation of innovations. *Academy of Management Journal, 1*, 167-181. doi:10.5465/AMJ.2010.48037420

Townsend, B. K., & Wilson, K. B. (2009). The Academic and Social Integration of Persisting Community College Transfer Students. *Journal of College Student Retention: Research, Theory and Practice, 10*(4), 405 - 423. doi:10.2190/CS.10.4.a

Villara, E., & Albertína, P. (2010). 'It is who knows you'. The positions of university students regarding intentional investment in social capital. *Studies in Higher Education, 35*(2), 137-154. doi:10.1080/03075070902957080

Vygotsky, L. S. (1978). *Mind in society: The development of higher psychological processes.* (M. Cole, V. John-Steiner, S. Scribner, & E. E. Souberman, Eds.) Cambridge, Massachusetts: Harvard University Press.

Wasserman, S., & Faust, K. (1994). *Social network analysis: Methods and applications.* New York: Cambridge University Press.

Wellman, B., Salaff, J., Dimitrova, D., Garton, L., Gulia, M., & Haythornwaite, C. (1996). Computer networks associal networks: Collaborative work, telework and virtual community. *Annual Review of Sociology, 22*(1), 213-238. doi:10.1146/annurev.soc.22.1.213

Yang, H.-L., & Tang, J.-H. (2003). Effects of social network on student performance: Web-based forum study in Taiwan. *Journal of Asynchronous Learning Network, 7*(3), 93–107.

Yorke, M. (1991). Performance indicators: Towards a synoptic framework. *Higher Education, 21*(2), 235–248. doi:10.1007/BF00137076

Yuan, Y. C., Gay, G., & Hembrooke, H. (2006). Focused activities and the development of social capital in a distributed learning ''community''. *The Information Society, 22*(1), 25-39. doi:10.1080/01972240500388347