Social Capital in Online Environments: Effects of Social Structure on Academic Performance in an Online University

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Abstract
The idea of social capital as the value obtainable from an individual's social relationships has been used to study many organizational and social settings, but rarely virtual environments. We used data from an online higher education institution to examine how an individual's social capital derived from her position in the social structure influences her performance levels. We confirmed that social capital has a significant effect on achievement. Firstly, we found that centrality and cohesion in social networks have a positive effect. Secondly, we showed how the network structure counts and how diversity in relationships is important. Having access to heterogeneous peers also increases the performance level in learning processes. These findings suggest that the proven importance of social capital in face-to-face situations might be translated into virtual environments and support the need to build or enhance ICT-mediated students' social networks in distance learning.

Keywords: Social capital, virtual organizations, social networks, academic performance, online universities

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The fundamental idea behind the concept of social capital is quite simple: relationships matter. This notion has influenced our view of the social world since the 1920s. However, it has become increasingly important in the social sciences since Pierre Bourdieu and James Coleman established its theoretical foundations in the 1980s. In the last decades, many scientific works have shown how social links allow individuals and collectivities to access valuable resources in many ways while they perform their daily activities.

Nowadays, many of those activities are transferred, in part or entirely, from traditional settings to online environments. We may wonder if things will remain the same in the new scenario. Do social capital benefits translate unchanged into the online world? Are the diverse social capital influence mechanisms similar in virtual settings, or do they show some specificities? Do we need to revise our current social capital theories or build new "online social capital" theories?

Social relationships today take place as much in online environments as face-to-face. Therefore, social networks also form online, and, as a consequence, social capital may be accumulated in that way. For instance, the effects of social capital have been shown as necessary in social media as in the "real world" (Arampatzi et al., 2018; Burke & Kraut, 2016; Ellison et al., 2007; J.-H. T. Lin, 2019; Phulari et al., 2010). Moreover, things may work differently than in traditional environments (Dunbar, 2016; Steinfield et al., 2013). The singular characteristics of social media may allow, for instance, new mechanisms of social capital use to appear or the power of traditional ones to rise exponentially. One clear example is the increasingly important figure of the "influencer" on Twitter and other social sites (Freberg et al., 2011). Does social capital work differently online?

Our aim here is to contribute to answering these questions by examining the case of a specific online environment: a technology-mediated distance university. Two main reasons support our choice. First, social capital influences the educational processes in academic institutions. In the literature, we can find many accounts of that in different educational and learning environments (Cho et al., 2007; Coleman, 1988; Krasny et al., 2015; Maroulis & Gomez, 2008; Ramírez Ortiz et al., 2004; Söllner et al., 2018). Second, as opposed to the case of social media, online education has its clear traditional counterpart, which facilitates the comparison of the effects of social capital in each case.

This paper will present theoretical ideas about how social capital may influence performance in online environments. Following the idea that social capital gives access to new resources through social connections, we will examine two primary resources that might be useful in an online community: information and social cohesion and the mechanisms through which they work. Then, we will test those ideas in a completely online academic environment: a virtual university.

The main findings we will present show how social capital is indeed still crucial in online settings. Based on the structure of the social network, we will suggest two social capital-based mechanisms that may act simultaneously: access to information and creating a cohesive local environment for individuals. We will see that both of them may contribute to improving performance in an online environment like an internet-based distance university.

The paper is structured as follows. First, we will introduce the concept of social capital and how we will approach it in our study. Second, we will present some ideas on the mechanisms by which social capital may influence performance, specifically in online settings. Based on that, we will put forward some propositions on the effects of social structure on individual performance in online environments. After that, we will describe our research setting, the methodology we have used, and the results obtained. We will finish with a discussion of our results and some conclusions.

Theoretical Framework

Social Capital

The Social Capital Perspective

The concept of social capital relies on the idea that "social networks have value" (Putnam, 1995). Networks enable people to cooperate for mutual advantage. This advantage comes from networks granting access to the resources possessed by the other individuals to whom one is connected. Social capital gives access to additional resources through social network connections (N. Lin, 2001b).

In the beginning, the term "social capital" appeared just as a metaphor based on its similarity to other forms of capital previously defined in the literature, like economic capital (Marx, 1867) or human capital (Becker, 1964). Much later, a similar process would occur with the concept of intellectual capital (Brooking, 1996; Edvinsson & Malone, 1997). The metaphor implied that social links are profitable; one could invest in them and expect a return, as with any other form of capital. Different kinds of capital provide individuals or communities with diverse resources. While the other types of capital usually give way to resources that belong to the actor that will put them into use, in the case of social capital, those resources typically belong to other actors that the focal actor accesses through her social links.

However, in the 1980s and 1990s, the metaphor gave way to more serious attempts to build a theoretical apparatus around the concept of social capital. Three seminal figures contributed decisively to give it contemporary significance: Pierre Bourdieu, James Coleman, and Robert Putnam (Field, 2008). Although each tackled the issue from a different angle, making it difficult to conciliate their respective theoretical frameworks, their works popularized social capital in sociology and other social sciences. The first two authors and later developments of their ideas constitute the foundations of the concept of social capital we will use in this work.

Bourdieu (1986) was the first sociologist to systematically analyze the concept of social capital. He approached the idea from an individualistic point of view. The social capital possessed by an individual is the sum of actual or potential resources that he can access through his network of relationships: "by virtue of possessing a durable network of more or less institutionalized relationships of mutual acquaintance and recognition" (Bourdieu & Wacquant, 1992, p. 119). Deeply influenced by Marxist sociology, Bourdieu saw social capital—like other kinds of capital, including what he called cultural capital—as a mechanism by which social inequality was created and reproduced. This way, the dominant class could maintain and reproduce group solidarity and preserve its dominant position (Bourdieu, 1986; N. Lin, 2001b). A remarkable aspect of Bourdieu's view is that he distinguishes two elements in social capital: on the one hand, the social relationship that makes it possible for the individual to access resources, and, on the other hand, the quantity and quality of those resources (Portes, 1998). Bourdieu's ideas on the suitability of examining networks based on online interactions have lately been acknowledged, among others, by Julien (2015).

Coleman was mainly interested in social inequality and its effects on academic achievement in schools, and he developed his idea of social capital after several studies on this subject (Coleman, 1990). He identified social capital as critical in creating human capital in the education system (Coleman, 1988). His idea of social capital was less sophisticated than Bourdieu's since he equated it to the set of resources that may be accessed through social relationships. In his view, social capital is a set of entities, each consisting of some aspect of social structure, that facilitate specific actions for the individuals within that structure (Coleman, 1990, p. 302). He proposed that social capital is intangible and has three forms: (a) level of trust, (b) information channels, and (c) norms and sanctions that promote the common good over self-interest (Coleman, 1988). His idea of social capital bridged the individual and the collective views and tended to see it as a collective good. Coleman's works gave rise to many studies about the influence of different aspects of the families' social capital on children's education (Acar, 2011; Dika & Singh, 2002; Novak et al., 2018). However, as we will see below, it is not until recently that some authors have started investigating the influence of the actual students' social capital, especially in higher education contexts.

Social capital can be considered from two different points of view: the individual and the collective (Kadushin, 2012; Portes, 1998). Individual-level social capital is the social capital of individuals that allows them to access networked resources (Bourdieu, 1980; N. Lin, 2001a). The collective-level social capital view refers to social capital as an attribute of social systems like communities and organizations (Coleman, 1990; Putnam, 1995). We will focus our analysis on the individual-level social capital since we are interested in understanding how the structure of the social networks gives access to resources to the individual members of an online community. We aim to relate the benefits that social capital mechanisms provide to various aspects of the structure of social networks. Based on Coleman's theory, Sandefur and Laumann (1998) identify three benefits of social capital: access to information, influence and control, and social solidarity. We will rely on this classification of benefits for our analysis.

Benefits of Social Capital

Social and organizational research has shown the importance of social capital for the performance of individuals, groups, and organizations. Social actors use the different kinds of resources they can reach through their social networks to increase their effectiveness and improve their efficiency. In his seminal work about weak ties, for instance, Granovetter (1973) showed how social links outside of their close social surroundings allowed individuals to get valuable and helpful information, in that case, about the job market. Later, Coleman (1988, 1990) stated the influence of social capital in creating human capital is a critical performance factor. This view hinges on the idea that when everyone is connected to everybody else, information flows easily, and the transfer and creation of knowledge are more effective. Network closure, thus, is the primary source of social capital.

By introducing the concept of structural holes, Ronald Burt (1992, 2005) explained how social structure could be, in fact, a source of competitive advantage for individual actors in another way. Some privileged positions in the social network make it possible to reach, transfer, or hoard information at the convenience of the individual occupying them, which allows him to engage in brokerage activities for his benefit. Structural holes would constitute, therefore, a source of social capital more critical than closure (Burt, 2000, 2001).

Since then, many other contributions have assessed the positive effect of social capital on performance in different kinds of processes: learning (Leana & Pil, 2006), career success (Seibert et al., 2001), cooperative strategy (Dyer & Singh, 1998), product innovation (Tsai & Ghoshal, 1998), intellectual capital development (Nahapiet & Ghoshal, 1998), well-being (Burke & Kraut, 2016), or health (Billedo et al., 2019). In a more general study using pooled data from an international comparative survey in 28 countries, Finsveen and van Oorschot (2008) found that, although weak, there is a positive relationship between network characteristics and the people's capacity to access resources through this network, i.e., their social capital.

Social Capital in Learning and Education

The theoretical developments of the concept of social capital carried out by Bourdieu and Coleman originated in explaining the educational process performance. Bourdieu developed his ideas on cultural and social capital as alternative explanations of unequal academic achievement (Bourdieu, 1986). Coleman used his social capital idea to explain aspects like the incidence of dropping out of school (Coleman, 1988). It is normal, thus, that both theoretical frameworks and other views of social capital based on them have been extensively used in the learning and education literature, with Coleman's framework guiding most of the work (Dika & Singh, 2002; Sun, 1999). This trend has increased in recent decades (Steinfield et al., 2013).

In their thorough review of the applications of social capital in educational literature, Dika and Singh (2002) identify three main areas of research: (a) social capital influence on learning achievement (grades, test scores); (b) social capital influence on educational attainment (graduation, college enrollment); and (c) psychosocial factors that affect educational development (engagement, motivation, self-concept).

Within the first area of research, social capital influence on educational achievement, several contributions have appeared in the last years looking at the impact of the student's social capital on their academic performance in higher education (Demir, 2021; Mishra, 2020), in contrast to the effect of individual characteristics like psychological capital (Barratt & Duran, 2021). Different approaches and methodologies, both qualitative and quantitative, have been used, for instance, to tackle issues like the academic and professional identity formation in higher education (Jensen & Jetten, 2015), the influence of academic peers on academic achievement (Hasan & Bagde, 2013), or the role of knowledge sharing as a mediator between the three dimensions of social capital proposed by Nahapiet and Ghoshal (1998) and academic performance (Aslam et al., 2013).

With this work, we also aim to contribute to the first area of research identified by Dika and Singh. However, we will do that by conceptualizing social capital as access to institutional resources, closer to Bourdieu's view than to Coleman's. This approach will allow us to use network structure as in the study of social capital (Kadushin, 2012; N. Lin, 2001b) and overcome some of the limitations of Coleman's concept. Moreover, we will examine a new environment not often present in the literature: online higher education.

Social Capital in Online Environments

Most of the studied effects of social capital have been observed in settings where social interactions occur mostly face-to-face or through traditional means. We may wonder whether the conclusions reached in those studies still hold for online settings, where most—if not all—of the contact between individuals is over technological networks. Is it possible that the effects of social capital are different online? Is social capital still relevant for performance in online environments? Is it maybe even more important? Are the mechanisms of social capital influence different from those in place at more "traditional" turfs?

Like their face-to-face counterparts, online social interactions give rise to social networks and, therefore, offer the possibility of leveraging social capital. Nevertheless, some differences between face-to-face and online environments are beginning to be present. We know, for instance, that in online communities formed through social media sites, concepts like "friendship" take a completely different meaning and that access to social capital might be diverse (Ellison et al., 2007; Steinfield et al., 2013). However, those communities are not the place where performance is usually measured. It is advisable to examine other kinds of online environments where individuals interact socially but simultaneously have specific tasks to perform.

In one of the few research strands tackling this issue in the literature, Ahuja and Carley (1999), after studying the case of a virtual research group, conclude that virtual organizations are similar to traditional organizations in some ways but different in others. Based on this, they advocate for further studies in this subject matter. Later, Ahuja et al. (2003) maintain that the different roles (functional, status, or communication) of virtual R&D groups have direct effects on individual performance and indirect effects through individual centrality.

In one of the few studies comparing face-to-face with online higher education processes in detail, Lobel et al. (2005) detect substantive differences in communication patterns among students, particularly, in the structure of social networks. Later, several authors investigated different kinds of mechanisms by which social capital is formed in online settings, for instance, social presence (Oztok et al., 2015), language and communication (Joksimović et al., 2018), cultural capital and techno-capital (Hamilton et al., 2023), or core self-evaluation and online interaction quality (Diep et al., 2017). However, there is a lack of studies that empirically analyze the effects of social capital in online higher education settings, attending to the actual structure of social networks. We aim to contribute to covering this gap.

Recent Studies on Academic Performance in Online Environments and Social Capital

The study of academic performance and the factors influencing it is a long-standing topic in the learning and education field (Honicke & Broadbent, 2016; Vermunt, 2005; Wentzel & Wigfield, 1998). Recent studies have focused on the relationship between the academic performance of higher education students and a wide range of specific factors in specific contexts, such as student loans for financially disadvantaged students (Huang et al., 2018), student engagement (Ogunsakin et al., 2021), introduction of new teaching methodologies (Al Shloul et al., 2024; Cabrera-Mejía et al., 2021), emotions (Camacho-Morles et al., 2021), amount of coursework in online courses (Motz et al., 2021; Shea & Bidjerano, 2019), social disparities (Helbling et al., 2019), past performance (Nadasen & List, 2016), etc. For our research, we will focus more specifically on studies conducted mostly in online environments where social capital, as explained in previous sections, is a significant factor considered. We consider online environments broadly, including fully online environments, blended learning environments, and emergency remote environments (such as those suddenly created because of COVID-19 lockdowns).

Many studies in small samples (tens of students) or medium samples (hundreds of students) shed some light on the relationship between performance and some specific facet related to social capital. For instance, Ensmann et al. (2021) conducted a qualitative study about the role and importance of the social presence of students in emergency-created online environments because of the pandemic. They use the concept of social presence proposed by Whiteside (2007), which is based on Wenger's ideas about communities of practice and social learning (Wenger & Snyder, 2000). Yang and Tang (2003) conducted a quantitative study and found evidence about the influence of the so-called friendship networks, advice networks, and adversarial networks on academic performance. Both Yang and Tang (2003) and Ensmann et al. (2021) are conducted on a small sample of students and devoted to specific concepts related to social capital.

Gay and Betts (2020) conducted an experimental study in a broader online setting (hundreds of students). They concluded that high-touch strategies, based on ideas of community development by Palloff and Pratt (1999) and Stanford-Bowers (2008), positively influence academic achievement. Also, Iqbal et al. (2021) conducted a survey study over a medium sample of hundreds of students and found a positive influence of academic social networking sites on academic performance.

Another recent stream of literature is represented by Yagci (2022) and previous related studies, such as Bernacki et al. (2020), Musso et al. (2020), Waheed et al. (2020), Ahmad and Shahzadi (2018), Xu et al. (2019), and Burgos et al. (2018). In broad terms, this research builds up and tests models to predict or explain academic performance in online, blended, or face-to-face contexts. They use different proxies for academic performance, such as grades, degree completion, dropout, etc. They propose different explanatory variables such as previous marks, demographic variables, logs in the learning management systems, learning strategies, internet usage, etc. They use algorithms such as machine learning, deep learning, or logistic regression. They work mostly with medium datasets of hundreds, with the exceptions of Waheed et al. (2020) and Xu et al. (2019), that work with huge datasets of thousands. None of these studies uses explanatory variables explicitly based on social capital. The only ones to consider demographic variables are Waheed et al. (2020), but no significance of gender or age is found related to performance.

Our work aims to build on this stream of literature devoted to models, combining a selection of explanatory variables previously used, including past grades, gender, and age, as well as social capital. It should be noted that we will work with a much larger dataset than the ones used in the previous studies mentioned and that it comprises students of a wider range of degrees.

Social Structure and Performance

<u>Tie Structure</u>

As we have seen in our literature analysis, social capital has been shown to affect academic performance. This study aims to investigate the specific mechanisms through which social capital has this influence. For this, we will examine the three possible benefits of social capital identified by Sandefur and Laumann (1998): access to information, influence and control, and social solidarity.

Reach and Centrality. The first benefit of social capital that we consider is access to information. Indeed, accessing timely and trustworthy information has a definite positive effect on performance. The ability of a social actor to access that information will depend, structurally, on her centrality, i.e., on the possibility of reaching the other actors easily in the network. Among the large number of centrality measures offered by the literature (Borgatti et al., 1998; Wasserman & Faust, 1994), we choose **degree centrality** for our study since we assume that in online environments, especially those in which individuals pursue some definite objective, interactions are purposeful and direct. Because of that, we discard betweenness centrality (that measures to what extent the actor may intercept information flows) and closeness centrality (that measures the proximity to the rest of the actors in the network). Thus, we derive the following hypothesis:

H1: Actors with a higher degree of centrality will perform better.

Brokerage and control. In structural terms, influence and control may be associated with the possibility of brokerage through the spanning of structural holes. Possible measures of that capability in agents would be Burt's effective size or constraint (Burt, 1992). However, both measures are a function of ego network density (i.e., transitivity). In essence, social capital due to the brokerage capacity of an actor increases with the number of other actors she can access and decreases with the extent to which those are connected. Thus, we may omit direct measures for structural holes since we will use the transitivity measure. Instead, we will use the combination of **degree centrality** and **transitivity** as a proxy for brokerage capacity (Borgatti et al., 2013, p. 276).

If this benefit of social capital is relevant for performance in our online community, the following hypothesis will hold:

H2: The performance of an actor will increase with degree centrality and decrease with transitivity.

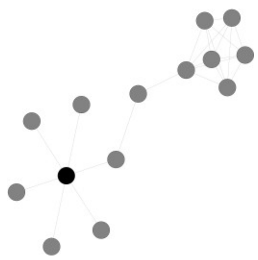
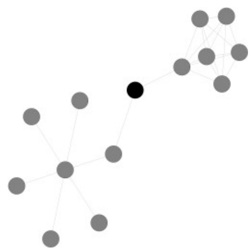
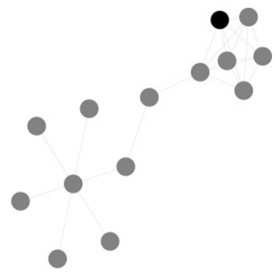
Cohesion. Social solidarity in online communities will be a benefit of social capital, leading to the improvement of performance as long as individuals build with those with whom they are in touch, have a common set of values, and develop trust (Sandefur & Laumann, 1998). Structurally, that will be more likely if they have a cohesive ego network, i.e., when their **transitivity** measure is high. Thus, we hypothesize:

H3: Individuals with a higher level of transitivity in their network will perform better

Figure 1 shows the three benefits of tie structure and the associate measures we use.

Figure 1

The Structure-Related Benefits and Their Associated Measures

	Reach and centrality	Brokerage and control	Cohesion
Benefit	Access to information	Influence and control	Cohesion
			
Structural measure	Degree centrality	Burt's redundancy (structural holes) ~ Degree centrality – Transitivity	Clustering coefficient (transitivity)
	$k_i = \sum_{i=1}^{n} A_{ij}$	$R_i = f(k_i, C_i) \sim k_i - C_i$	$C_i = \frac{(\#\, triangles\ with\ i)}{(\#\, pairs\ neighbors\ i)}$

Note. Darker nodes in the example graphical representations correspond to the actors with a higher value for the respective measure (see the Measures section).

Tie Quality

Up to this point, we have related social capital benefits in online environments to the social network structure, considering all ties equally important. However, the importance of one actor's ties depends obviously on the actor's characteristics at the other end of that tie. We now introduce the idea that an individual's social capital will depend not only on the form of its ego network structure. It will also be affected by the quality of that network in terms of the attributes of her alters.

<u>Diversity</u>

We may assume, for instance, that those actors with a higher degree of heterophily in their relationships will have access to more diverse sources of information or that they will be able to build more supportive entourages. Thus, diversity will positively affect their performance (Granovetter, 1973; Page, 2007; Reagans & Zuckerman, 2001). We have, therefore, the following hypothesis:

> **H4:** An actor's performance will increase with the level of heterophily in her social network ties

We may define different flavors of heterophily attending to diverse attributes of the students. In this case, we use gender, program, and age because these attributes have been found relevant in the literature. This allows us to split H4 into different sub-hypotheses:

H4a: An actor's performance will increase with the level of gender heterophily in her social network ties
H4b: An actor's performance will increase with the level of program heterophily in her social network ties
H4c: An actor's performance will improve with the level of age heterophily in her social network ties

Preferential Partners

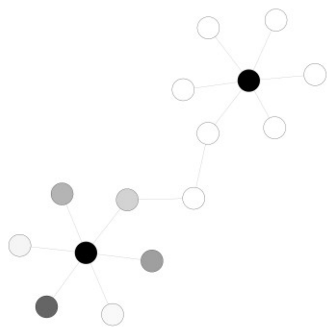
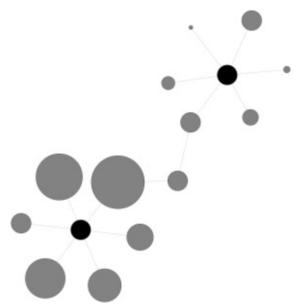
We may also assume that those actors who tie with others with a high **level of performance** will perform better (Hasan & Bagde, 2013). The following hypothesis captures this idea:

H5: An actor's performance will increase with the average level of performance of her social network ties

Figure 2 shows the two benefits of tie quality and the measures we use to assess them.

Figure 2

Tie-Related Benefits and Their Associated Measures

	Diversity	**Preferential partners**
Benefit	Draw upon knowledge heterogeneity (age, gender, program)	Learn from more knowledgeable others
		
Structural measure	Link heterogeneity	Positive performance difference
	$h_{ij} = \|\|x_j - x_i\|\|$	$d_{ij} = x_j - x_i$

Note. In the example graphical representation of the diversity benefit, the top dark node is surrounded by nodes of different characteristics. Therefore, it has higher link diversity than the dark node at the bottom of the image. In the example for preferential partners, the top dark node is surrounded by nodes with a higher level of performance (represented by their size), which implies a higher performance difference with its contacts, contrary to what happens with the bottom dark node. We use for them the measures of link heterogeneity and positive performance difference, respectively (see the Measures section).

Research Design

Email Networks

Informal social networks play an essential role in the internal dynamics of organizations, and their study provides interesting insights for organization scientists (Borgatti & Cross, 2003; D. Krackhardt & Hanson, 1993; D. J. Krackhardt et al., 2001). However, describing real social networks is not easy due to the difficulties associated with data gathering. Traditional methodologies relying on surveys or interviews are often challenging to interpret and represent a high cost in terms of time. Nowadays, electronic communication systems like mobile phones, email, instant messaging, or social media may provide a large amount of data on social interaction in the form of data stored in log files. This information presents a high degree of accuracy and thoroughness and is ready to be used and analyzed by automated means. Through the use of this information, it is quite feasible to identify and study social networks in diverse settings while being respectful of privacy issues (Kitchin, 2014).

Of course, not all social interactions occur electronically, and analyzing the networks built with data coming from electronic communication systems gives only a partial vision of reality. In some modern organizations where these systems are generalized, though, this partial vision may provide quite accurate insights into the structure of the social fabric (Adamic & Adar, 2003). In the case of virtual organizations where all interaction occurs online, the social structure inferred through the analysis of electronic data must be logically closer to the real one.

For instance, information gathered from email systems at organizations where it is extensively used and becomes one of the main communication channels is particularly well suited for this purpose. With data collected by the email server about the sender and receiver of each message—which are present in any log file—it is possible to build an email social network. Instances of this kind of network have been used in the study of different aspects of social networks, namely network topology (Ebel et al., 2002), search strategies (Adamic & Adar, 2005), information diffusion (Wu et al., 2004), spread of computer viruses (Newman, 2002), temporal dynamics (Eckmann et al., 2003), the strength of connections (Caldarelli et al., 2003), and community structure (Guimera et al., 2006; Tyler et al., 2003).

Research Setting

To conduct our empirical research, we used the case of an online higher education institution, the UOC (Universitat Oberta de Catalunya—Open University of Catalonia), with headquarters in Barcelona (Cobarsí, 2008). We characterized the informal social network formed by the students of different undergraduate programs at UOC and relate it to their academic performance. UOC was founded in 1994 by the Catalan government and offers various undergraduate and graduate programs in Catalan, Spanish, and English. At the moment our data were gathered, UOC had more than 40,000 students, more than 2,000 members of the faculty (from them, about 200 were full-time academics, and the rest were academic collaborators on a part-time basis), and around 400 administrative personnel. Faculty at UOC is distributed among several *Estudis* ("faculties") representing different academic areas. All of UOC's courses are imparted online, making use of an in-house developed Learning Management System (LMS), the *Campus Virtual* ("Virtual Campus"), which includes an email system. This system is also meant for internal communication among faculty or administrative personnel members. The Campus Virtual is extensively used due to the virtual character of the organization. A single LMS and a single educational model guarantees high technological and pedagogical standardization across programs.

We used the UOC network in our study for several reasons. On the one hand, it was a genuinely virtual organization in which students and faculty communicate among themselves almost exclusively through online channels, be it the classroom web spaces or the university's email system. Therefore, most informal interactions occurred through UOC's email system. The email social network was a valid approximation of the underlying general social network. On the other hand, the results of the students enrolled in the different programs in the form of grades obtained from the registrar's office provided us with an adequate measure of individual performance.

Dataset and Network Definition

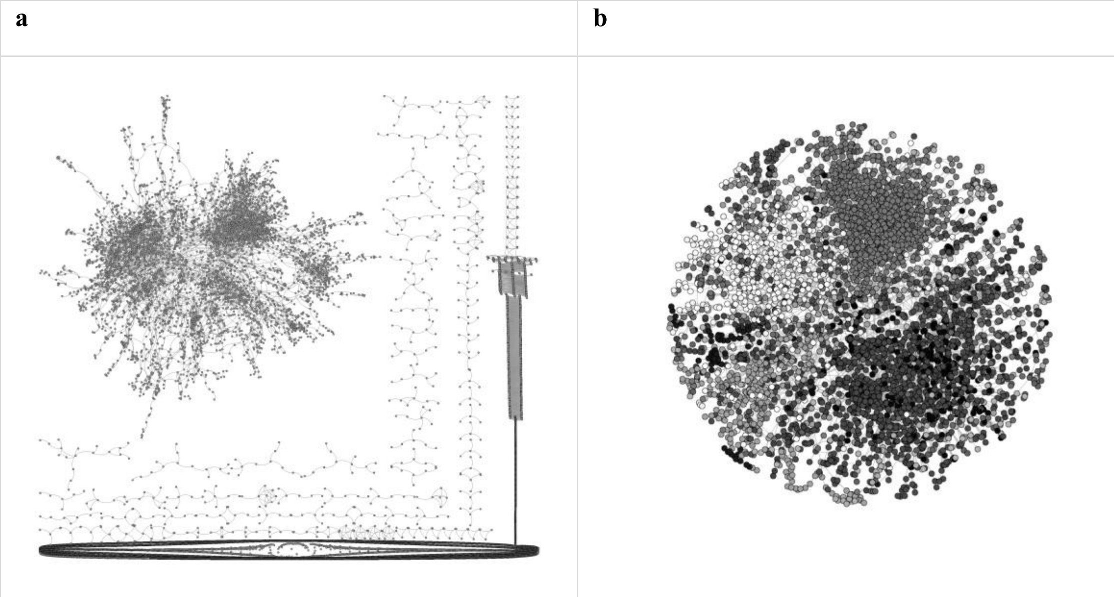
For the representation of the email social network of UOC, we used a database containing the log data recorded for one month. In that time, 854,522 messages were recorded, from which 462,033 can be considered internal (from one UOC email address to another UOC email address). We obtained this database from the UOC's IT department, which approved it after ensuring the data would be anonymized.

To obtain a measure of the performance of students in the period studied, we made use of the academic results for that semester and the previous one. We also gathered some features of the individual profiles of students to be used as control variables: age, gender, program to which they belong, and the number of courses to which they have enrolled in the focal semester.

To build the social network we used in our study, we selected all students' email user addresses. We considered that a link exists between two users if they had exchanged at least two messages in one month and, second, they had exchanged messages in both directions. This undirected network represents, thus, the social network of all the undergraduate students at UOC (see Figure 3a). It is a considerably sparse network composed of 18,857 nodes and 8,327 links. It can be seen in the structure of the greatest component (see Figure 3b) that there is a relevant percentage of links between students of different education programs.

Figure 3

Graphical Representations of the UOC Students' Email Network



Note. In (a), we show all network components, with a large greatest component and an important number of smaller components. In (b), we represent the greatest component. Node shades distinguish students from different education programs.

Measures

As a dependent variable, we will have our object of study: **academic performance**. Adopting the same practice of several of the works we have described in our literature review, we use as a proxy of academic performance the average of the grades obtained by UOC students in the spring semester of the academic year. Each student enrolled in a course is graded with a final mark between 0 and 10. The student's overall grade is the average of her grades in the courses she has been enrolled in. This measure represents, therefore, the student's semester GPA. These data are collected from the university registrar's office information system and anonymized appropriately. Academic performance is represented in a ratio scale from 0 to 10.

We estimate student grades using the following usual linear model:

$$Y = \boldsymbol{\beta}\mathbf{X} + \varepsilon$$

where Y is the dependent variable, β a vector of parameters for the effects of independent and control variables, $\mathbf{X}$ is the vector of independent and control variables, and ε is the error term.

We make use of five control variables. Firstly, the **age** and **gender** of students. Among the few additional pieces of information we could gather about the students, those that showed relevance to individual performance were those relevant to our preliminary analysis. Besides, these explanatory variables have been identified in the literature as personal variables that influence academic performance (Vermunt, 2005). As mentioned above, age and gender will also be used to define two different flavors of heterophily in hypotheses H4a and H4c.

Age is calculated using the students' date of birth, which the registrar's office provided. It is represented in a ratio scale. The ages of the students present in the final sample range from 18.33 years to 73.42 years, with a mean of 33.92 years. Gender is provided by the same source and is represented in a nominal scale (M for male, F for female). In the final sample, there are 6,989 females and 6,912 males.

We also use the **number of courses taken** by each student. The academic performance of individual students may be affected by the number of courses taken because not all students cope with the same workload in a semester. The performance of students taking a higher number of courses may be affected because they can devote less time to each of them. Again, these data are provided by the registrar's office.

We also control for the students' average grades **in the previous semester**. As in the case of the dependent variable, these data represent the previous semester's student GPA and are provided by the registrar's office. It helps to account for students' constant characteristics that would be significant predictors of academic performance but are outside our disposal, i.e., intelligence, work capacity, or level of competency previously developed. It will also contribute to establishing the causality in the detected effects beyond the mere correlation.

Finally, we control for the **academic program** in which each student is enrolled. There are 17 programs represented in our sample. This measure is represented on a nominal scale, with a category for each program. The academic program allows us to define a new heterophily flavor used in hypothesis H4b. Students from different programs may behave quite differently regarding social relationships, especially when they belong to distant knowledge areas like, for instance, engineering and humanities. Moreover, this avoids the need for standardizing grades to account for possible differences in program grading policies.

The UOC registrar's office provides all the above measures after ensuring the data will be anonymized. Of course, the anonymization codes used are the same as those used for the network database provided by the IT department. Our work does not involve the direct participation of human subjects, and we use only secondary data.

The first set of independent variables we use are purely network measures. As stated before, we will use degree centrality and transitivity. For **degree centrality**, we employ the definition proposed by Freeman (1979), as presented by Wasserman and Faust (1994). The degree centrality of an actor is just the number of links of that actor:

$$C_D(n_i) = \sum_j x_{ij} = \sum_i x_{ji}$$

where n_i represents the node i and x_{ij} represents the adjacency matrix of the network. **Transitivity** at the vertex level (or local clustering coefficient) is defined in Watts and Strogatz (1998) as:

$$C_i = \frac{\text{number of triangles connected to node } i}{\text{number of triples centered around node } i}$$

where a triple centered around node i is a set of two edges connected to node i. We obtain the network measures from the analysis of the network described in the previous section.

The second set of independent variables are combined measures relating to the ego network structure of the focal individual with attributes of her connections in that ego network. **Gender heterophily** accounts for the ratio of individuals of the opposite gender in the focal individual ego network. A male actor having all his connections with other male actors will have gender heterophily 0. If he is connected only with female actors, he will have gender heterophily 1. Similarly, **program heterophily** will measure the ratio of connections with programs different from the one in which the focal individual is enrolled. **Age heterophily** measures the average of the absolute differences in age between the focal agent and her connections. Finally, **performance difference** accounts for the average difference in performance between the focal actor and her connections measured in the grades scale. The performance difference will be positive if the average of the alters' grades is higher than the ego grade and negative in the opposite case.

Data Analysis

To perform the linear regressions, we selected the students from 17 different programs for which we have data corresponding to all the variables used, resulting in a total *N* of 13,901 students. Network measures are calculated in the whole network containing all students before selecting.

We use the standard linear model to calculate the regression coefficients. However, we cannot use the classical significance tests to test for those coefficients. This is because we are testing node-level (in terms of social network analysis) hypotheses in a social network environment. Here, we do not have a sample, but the entire population and the university is a "sample of one" chosen non-randomly. We are dealing with the whole network (and not just a sample), and our data do not seem to fulfill the normality assumption (the Shapiro-Wilk normality test for our best model gives $W = 0.9431$, $p < 2.2e\text{-}16$).

As Borgatti et al. (2013) point out, the classical significance is not adequate in these circumstances, and it is safer to run a randomization test. They advise running ordinary least squares as usual to obtain regression coefficients but constructing the significance values using the permutation technique. Thus, we follow their suggestion and use randomization to determine the significance tests instead of the usual procedure. We apply the bootstrapping methodology to calculate 95% Confidence Intervals as described in Fox (2008) and Fox and Weisberg (2011).

Data analysis and calculations have been made using the *igraph* network analysis package, the R statistical environment, and the Wolfram Mathematica™ software.

Table 1

Results of Regression Analysis Predicting Academic Performance

Variable	Model 1				Model 2				Model 3				Model 4			
	B		***Bootstrap 95% CI***		B		***Bootstrap 95% CI***		B		***Bootstrap 95% CI***		B		***Bootstrap 95% CI***	
			LL	*UL*			*LL*	*UL*			*LL*	*UL*			*LL*	*UL*
Controls																
Age	0.029	*	*0.024*	*0.034*	0.028	*	*0.023*	*0.033*	0.023	*	*0.018*	*0.027*	0.223	*	*0.018*	*0.028*
Gender[a]	-0.066		*-0.146*	*0.024*	-0.037		*-0.123*	*0.048*	-0.065		*-0.143*	*0.019*	-0.039		*-0.118*	*0.045*
Number of courses taken	0.019		*-0.008*	*0.048*	-0.019		*-0.050*	*0.011*	-0.019		*-0.047*	*0.011*	-0.022		*-0.050*	*0.005*
Avg. grade previous semester	0.462	*	*0.445*	*0.478*	0.453	*	*0.435*	*0.474*	0.404	*	*0.386*	*0.423*	0.401	*	*0.382*	*0.421*
Network measures																
Degree					0.091	*	*0.073*	*0.111*	0.064	*	*0.050*	*0.081*	0.173	*	*0.145*	*0.213*
Transitivity					0.389	*	*0.224*	*0.555*	0.368	*	*0.247*	*0.481*	0.373	*	*0.102*	*0.550*
Combined measures																
Gender heterophily									0.378	*	*0.269*	*0.471*	0.542	*	*0.369*	*0.654*
Program heterophily									0.115		*-0.003*	*0.222*	0.253	*	*0.071*	*0.393*
Age heterophily									0.003	*	*0.002*	*0.014*	0.008	*	*0.005*	*0.035*
Performance difference									0.520	*	*0.500*	*0.541*	0.480	*	*0.449*	*0.508*
Interactions																
Degree × Gender heterophily													-0.156	*	*-0.209*	*-0.114*
Degree × Program heterophily													-0.134	*	*-0.183*	*-0.080*
Degree × Age heterophily													-0.005	*	*-0.009*	*-0.003*
Degree × Performance dif.													0.018	*	*0.007*	*0.030*
Transitivity × Gender heter.													-0.177		*-0.512*	*0.169*
Transitivity × Program heter.													0.187		*-0.140*	*0.509*
Transitivity × Age heter.													-0.000		*-0.020*	*0.029*
Transitivity × Performance dif.													0.091	*	*0.020*	*0.150*
Intercept																
Constant	2.061	*	*1.833*	*2.283*	2.178	*	*1.944*	*2.405*	2.620	*	*2.390*	*2.846*	2.601	*	*2.385*	*2.837*
R^2	0.2253				0.2326				0.3241				0.3277			
Adjusted R^2	0.2241				0.2314				0.3228				0.3260			

Note. N = 13,901.
[a] 0 = female; 1= male.
* Significant with bootstrap 95% CI.
An additional control variable, program, is omitted from the table.

Results

Table 1 shows the results obtained from the different regressions performed. Model 1 uses only control variables and explains about 22.5% of the variance. From the four control variables used, only two, age and average grade in the previous semester, contributed significantly, both positively. In Model 2, we achieve an additional 1% in R^2 by including the two network measures, degree and transitivity. Both of them have a significant positive effect. Model 3 also includes the combined measures. Three of them (gender heterophily, age heterophily, and performance difference) significantly affect performance positively. This model explains nearly 32.4% of the variance, which signifies a substantial increase from the previous model.

In Model 4, we introduced an additional analysis by including all possible interaction terms between network measures and combined measures. This new model slightly improves the variance's explanation level to 32.8%. Looking at the regression coefficients in this model, we may extract several consequences. The variable *age* significantly contributes to academic performance with a coefficient B = 0.223, which belongs to the 95% confidence interval CI = [0.018, 0.028]. That means that every year of age makes a student, on average, improve their grade by 0.223 points. *Gender*, on the contrary, does not show a differential contribution since its coefficient lies out of the confidence interval (B = -0.039, CI = [-0.118, 0.045]). The same happens with the *number of courses taken* (B = -0.022, CI = [-0.050, 0.005]). The student's courseload does not seem to significantly affect academic performance. Contrarily, there is a strong effect of the *average grade in the previous semester* (B = 0.401, CI = [0.382, 0.421]). This is normal since we use this variable as a proxy of each student's competence level regardless of the circumstances of the studied semester.

Both network variables, *degree* (B = 0.173, CI = [0.145, 0.213]) and *transitivity* (B = 0.373, [0.102, 0.550]), show a positive effect on performance. Relying on the model we put forward in Figure 1, this means that two of the proposed mechanisms of social capital work. First, those students who occupy a more central position in their network perform better because they have better access to information. Therefore, H1 is supported. Second, students with a higher clustering coefficient (transitivity) develop a higher social cohesion that improves knowledge transfer and generation, supporting H3. Looking at both coefficients, we notice that the effect of social cohesion is more important than the effect of centrality.

The third mechanism proposed does not seem to work since this would require the presence of a structural hole, simultaneously a positive effect of degree centrality and a negative effect of transitivity. This means that influence and control are not important for performance in higher education settings. In our case, thus, H2 is not supported. However, this result might change in a business environment with higher competition.

All four combined measures have a significant positive effect. The initial three measures capture the first mechanism described in Figure 2: using diversity as a source of knowledge. In the case of *gender heterophily* (B = 0.542, CI = [0.369, 0.654]), it means that those students who have more relationships through the network with students of the other gender perform better. This is the strongest effect of the four combined measures. H4a is supported. A similar effect occurs for *program heterophily* (B = 0.253, CI = [0.071, 0.393]): students with more contact with colleagues in other programs perform better. Thus, H4b is also supported. *Age heterophily* (B = 0.008, CI = [0.005, 0.035]) also has a positive effect, although very small. Having contact with other students of different ages gives a slight plus in performance. This supports H4c. Finally, those students who mingle with others with higher capacities tend to perform better. This is captured by the performance difference variable (B = 0.480, CI = [0.449, 0.508]) and relies upon the mechanism of preferential partners represented in Figure 2. H5 is supported.

Only the interaction terms with the performance difference variable are significant and positive, which implies that the positive effect of having connections with better-performing students is enhanced when degree centrality and transitivity increase. The other three interaction terms with degree centrality are indeed significant but with a negative coefficient. This could point to a decrease in performance when actors have to maintain a higher number of connections when those have a heterophilic nature. Most of the interaction terms for transitivity are insignificant.

In Table 2, we summarize the hypotheses we have formulated above and whether they are corroborated or not.

Table 2

Hypotheses and Testing Results

	Hypothesis	**Test**
H1	Actors with a higher degree of centrality will have better performance	Supported
H2	The performance of an actor will increase with degree centrality and decrease with transitivity	Not supported
H3	Individuals with higher level of transitivity in their network will have better performance	Supported
H4a	An actor's performance will increase with the level of gender heterophily in her social network ties	Supported
H4b	An actor's performance will increase with the level of program heterophily in her social network ties	Supported
H4c	An actor's performance will increase with the level of age heterophily in her social network ties	Supported
H5	An actor's performance will increase with the average level of performance of her social network ties	Supported

Discussion

The results exposed above contribute to the literature in several ways. Firstly, they contrast the importance for academic performance in a purely online environment of different factors proposed in previous studies such as friendship networks or social learning (Ensmann et al., 2021; Yang & Tang, 2003), social disparities (Helbling et al., 2019), past performance (Nadasen & List, 2016), amount of coursework (Motz et al., 2021), or community development (Palloff & Pratt, 1999; Stanford-Bowers, 2008). Secondly, the more 'traditional' regression model developed here can be compared to the products of the late stream of literature proposing models based on AI algorithms like machine learning to predict academic performance (Ahmad & Shahzadi, 2018; Bernacki et al., 2020; Burgos et al., 2018; Musso et al., 2020; Waheed et al., 2020; Xu et al., 2019; Yağcı, 2022). Our model has the advantage of making the relationships between the variables understandable, which is hardly possible in AI models. However, in our view our most important contribution is establishing a series of structural measures that correspond to different mechanisms for obtaining benefits from social capital in a social network. Those benefits are access to information, influence and control, cohesion, drawing upon heterogeneity of social contacts, and learning from more knowledgeable others. They have shown their validity in our study, and we believe could be applied in other environments to assess the benefits of social capital.

Several meaningful insights from our work may be drawn specifically for virtual educational institutions. First, the mere structural position of a student in the social network influences her performance. This effect may be produced through two possible mechanisms: a position with higher centrality allows for better access to information, and a higher degree of cohesion may bring social solidarity into play through help or collaborative work. Both mechanisms work, although the latter's effect is much higher. Contrarily, influence and control by bridging structural holes do not work in this environment.

Second, even more important are the effects of the combination of structural position with the quality of a student's ties. Diversity of contacts in terms of gender, the program of study, and age (to a lesser extent) has a noticeably positive effect on student performance. Also, students with contacts with a higher level of performance show better achievement.

Third, interaction effects between centrality and diversity attenuate the mechanisms above, probably because a higher number of contacts lowers the importance of the diversity each contributed. Instead, the interaction effects between cohesion and diversity show nearly no impact.

Thus, our results stress the importance of social interaction for education. Consequently, we infer that distance learning institutions that offer social interaction instruments through ICTs will have an advantage over traditional distance universities, where there is often only one-to-one interaction between students and their teachers. It might make sense to think that the described behavior also applies to brick-and-mortar universities where interaction occurs face-to-face. The difficulties associated with capturing social interaction in those institutions may make the conclusions of studies like the present one about online universities particularly valuable.

Although a university is a specific kind of organization and an online university a particular sort of virtual organization, we believe that these ideas are consistent enough to be potentially generalized for any virtual organization and be subjected to test in further research.

It is interesting to point out that in a community where members have the objective of performing knowledge-related processes (e.g., students pursuing a higher education degree), a social structure that facilitates interaction and cohesion is more important for performance than a structure that makes it possible for individuals to benefit from structural holes. Therefore, we may deduce that performance is reinforced by dense interaction while the corresponding gains are distributed among all individuals involved. In this case, creating value through collaboration and knowledge generation would be more valuable than appropriating value, even for individual players by information brokerage.

What we see here might reflect that the structure of the social network is essential not only for the structural dimension of social capital (Nahapiet & Ghoshal, 1998). The relational and cognitive dimensions of social capital also rely, to some extent, on some structural characteristics of the network. In other words, individual structural features may mediate the effects of other social characteristics, as Ahuja et al. (2003) proposed.

These results should be generalized with caution. As stated before, it must be considered that students are not in a situation where they directly compete between themselves—although they may indirectly fight for scholarship grants or, in some grading systems, for higher rankings. Privileged access to information and control may probably result in more substantial benefits in other places with direct competition. There, the role of measures like structural holes might become more relevant.

Conclusion

We are aware of some of the limitations that affect the present study, especially if we pretend to generalize our results to other online and offline organizations. For instance, the social network that we identify through the email system might represent only part of the complete social network of students. However, that part may be significant in the specific case of an online university. Also, we did not have access to other control variables (i.e., rate of access to virtual classrooms) that could provide alternative explanations for performance or, at least, increase the soundness of the results.

Nevertheless, our results are robust enough to constitute a modest step in understanding how social networks influence performance in virtual organizations. Specifically, they shed some light on the learning processes at online higher education institutions. That is a social environment that has yet to be much studied, and that may show some features that will be common in most virtual organizations that will be more and more prevalent in the near future.

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Conflict of Interest

All authors declare that they have no conflicts of interest.

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