Social Networks 34 (2012) 47–58

Contents lists available at ScienceDirect

Social Networks

journal homepage: www.elsevier.com/locate/socnet

Social networks and spatial configuration—How office layouts drive social interaction

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ARTICLE INFO

Keywords:
Intra-organizational networks
Interaction patterns
Exponential random graph model
Office layout
Spatial configuration
Space Syntax

ABSTRACT

This paper analyzes the spatial dimensions of office layouts in diverse knowledge-intensive workplace environments based on the theoretical and methodological propositions of Space Syntax, and brings this together with the analysis of intra-organizational interaction networks. Physical distances between agents are modeled in different ways and used as explanatory variables in exponential random graph modeling. The paper shows that spatial configuration in offices can be considered an important but not sole rationale for tie formation. Furthermore, it is shown that spatial distance measures based on detailed configurational analysis outperform simple Euclidean distance metrics in predicting social ties.

1. Introduction

Beginning with proclamations by the sociologist Daniel Bell (1976) and later coined as 'spatial turn', 'renaissance of space' (Maresch and Werber, 2002) or the 'spatialization of social theory' (Massey, 1998), the concept of space has regained interest and attention throughout many social sciences, the humanities, arts, philosophy and cultural theory. The cultural geographer Edward Soja proposed that "the spatial dimension of our lives has never been of greater practical and political relevance than it is today." (Soja, 1996, p. 1) This has led to a growing research field considering various aspects of space in studies of social phenomena. Besides conceptual and theoretical contributions, it has been demonstrated empirically that space matters; for instance it has been argued that failing to control for the effects of spatial autocorrelation in regression models in cases with a spatial bearing can bias the estimation of other factors (Doreian, 1980, 1981; Dow et al., 1984; Mencken and Barnett, 1999).

Likewise, scholars have integrated geographical perspectives into the investigation of networks and the rationales for tie formation. They have conceptualized the spatiality of networks from a more theoretical point of view, as a combination of highly localized clusters with some additional random links to create global short path length in networks. This has subsequently been found to be a common structural feature of many real world networks by Watts (2004). These findings mean that location, or proximity between agents have become an interesting aspect to study in networks, since proximity gives rise to clustering, which in turn is seen as a main structural component of networks. Of course proximity in this sense is a broad term and is not confined to physical space. Localized clusters may also derive from structural considerations like reciprocity and transitivity (Holland and Leinhardt, 1972; Wasserman and Faust, 1994), or social similarity between agents, i.e. homophily (Blau, 1977; Ibarra, 1992; McPherson et al., 2001). Still space and physical proximity may play a crucial role in supporting tie formation and localized clusters and as such are factors worth investigating more closely.

This paper therefore sets out to explore how the study of physical space can prove a fruitful endeavor in network related research. An approach for including spatial data in exponential random graph models (ergm) as edge covariates is proposed. Four competing methods of measuring space and their effects on social interaction are compared with each other and against simple Euclidean distance, focusing on spatial micro settings within office buildings. The significance of the spatial effects in network ergm models suggests the importance of controlling for spatial distance in network models in corollary to the work on spatial autocorrelation in multiple linear regression.

Previous studies of organizational behavior and communication patterns within organizations have argued that physical proximity plays a major role for the probability of communication. In a seminal study by Allen and Fustfeld (1975) it was shown that coworkers that were separated by more than 25 m walking distance had a significantly lower probability of communicating with each other than those co-located closer to each other. More recently these results were confirmed by showing that highly frequent interaction (on a daily basis) did not reach further than 18 m on

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doi:10.1016/j.socnet.2011.05.005

average, as measured from someone's desk to another desk across a range of different office-based organizations (Sailer and Penn, 2009). However, these approaches did not take network structures into account, but only investigated pair-wise interaction frequencies. This paper now aims at filling this gap by bringing the study of network structures together with systematic and detailed investigations of spatial proximity between agents.

The argument will be developed in four consecutive steps: a first section will review literature linking physical space and networks in order to explore the existing knowledge base in the field more closely; the second section will briefly introduce the empirical case study material and the different methods employed in this paper, specifically focusing on the construction of spatial depth networks according to Space Syntax methodologies (Hillier, 1996; Hillier and Hanson, 1984); in the third section results from including spatial depth networks as parameters in exponential random graph modeling will be presented and discussed; before, finally, conclusions on the impact of spatial configuration on social network structures will be drawn.

2. The study of spatial dimensions of social networks

In the current network literature four main spatial and geographical perspectives can be distinguished, all of which cut across various disciplines and incorporate a broad diversity of research themes.

The first strand of the literature on spatial aspects of social networks is concerned with simulations and modeling. The notion of clusters, locality and distance among agents are used as a rationale for tie formation, assuming that ties emerge not only randomly, but also from local processes. Local social neighborhoods, i.e. geographical, social, cultural and psychological contexts are seen to make tie formation between agents more likely (Pattison and Robins, 2002). So-called 'settings' are incorporated into stochastic modeling (Schweinberger and Snijders, 2003), and it is proposed that physical distance may account for the vast majority of structure in large-scale networks (Butts, 2003). Additionally, networks modeled on the basis of a decreasing tie probability with increasing spatial distance between agents capture many properties of real world social networks (Wong et al., 2006). However, it has to be acknowledged that space is often used as a metaphor in this context; the most well-known being the concept of a 'Blau Space' (Blau, 1977; McPherson and Ranger-Moore, 1991), which denotes sociodemographic dimensions not necessarily related to physical space.

A second research perspective focuses on larger scale geographic space and the effects of proximity on inter-organizational collaborative networks, for example, in immediate disaster response networks (Bevc et al., 2009). Scholars have also argued that social network analysis can be fruitfully embedded into the discourse of economic geography and spatial clustering within an industry (Ter Wal and Boschma, 2009, in press).

The role of physical space in governing the quality and strength of social relationships in neighborhoods and communities is studied by a third group of scholars. An early study of couples and their social relationships in a student housing block at MIT (Festinger et al., 1950) proposed a so called propinquity effect, since it was found that physical proximity between people was the best predictor of friendship. With advances in communication and information technology it was argued that social relationships had become stretched by transportation and communication media beyond the borders of local neighborhoods, and that intimate social ties were often not local (Wellman and Leighton, 1979). Yet it was also shown that two thirds of frequent contacts were local (Wellman, 1996), that frequency of face-to-face contact and phone calls diminished with increasing distance and that distance had a significant impact on tangible support in social networks (Mok and Wellman, 2007). In essence, it was argued that communities were constituted in personalized networks that existed in physical as well as virtual places. Different types of spaces would complement each other and the character, intensity and importance of ties depended on the intrinsic qualities of space and the communication media used (Wellman, 2001, 2002). How different relationships created distinct spatial patterns was also shown in a study of village structures in Thailand, where economic networks spanned large distances and connected large clusters of villages, whereas educational or religious activities integrated smaller local communities (Faust et al., 2000). Similar effects of proximity on community structures, and the importance of spatial structure for the contagion of diseases was confirmed in studies in Ecuador (Bates et al., 2007).

The fourth group of contributions on spatial parameters and social networks focuses on intra-organizational networks. It was shown that the spatial configuration of an office shaped the formation and structure of intra-organizational networks, since different office layouts corresponded with distinct network structures (Sailer and Penn, 2007). Similarly, co-authorship network structures within an academic department were shown to be driven by distances separating agents, as well as office locations of agents (Wineman et al., 2009). In a police academy setting, social knowledge and friendship ties were fostered by training sessions in squads, which formed a major spatial embedding action within the academy, but also detailed seating arrangements in class rooms had a positive effect on tie formation (Conti and Doreian, 2010).

In summary, the study of spatial aspects of social networks can be considered an emerging and promising new theme in social network analysis across a variety of different topics and interests.

Two main conclusions can be drawn here: firstly, the nature of spatial influence seems probabilistic, i.e. spatial closeness seems to increase the probability for certain types of relationships. Physical proximity between agents seems to enhance the formation of certain types of ties, for example collaborations in economic clusters; proximity also allows the emergence of friendship relations and the enactment of local communities. However, social relations are hardly contained within spatial boundaries, since ties between agents may reach across physical space. Exactly this ability makes tie formation probabilistic regarding spatial proximity: in principal, ties can overcome the restrictions of physical space, but in certain contexts it may not be very likely.

Secondly, it can be concluded that empirical evidence on the impact of physical space on network formation is still scarce. Even though the review in this paper certainly claims no completeness, it is still rather an exception than the norm to consider aspects of physical space in social networks research. Another phenomenon comes into play here, i.e. operationalization and resolution of measuring physical space. It is commonly accepted that space should be modeled as simple Euclidean distance between agents. Distances are often measured 'as the crow flies', thus ignoring the real-life experience of a spatial system. This procedure may result in an appropriate degree of detail to investigate macro settings, yet is unsuitable to capture smaller spatial systems. For example, it may be more reasonable to consider two individuals working on the same floor of a building to be closer to each other than to individuals with closer Euclidean distance working on the floor directly below them. Following the analysis of Allen and Fustfeld (1975) on communication probability within a R&D company, being located on different floors was seen as a major disruption to co-worker communication. Additionally, in small scale environments not only distance matters, but also office layout. An open-plan office with hundreds of investment bankers in one space will create distinct spatial affordances for communication and interaction, as will a secluded cellular office environment typical for law firms. Extensive studies of office workers in Germany have shown that performance can vary significantly depending on the type of office environment (Kelter, 2001; Spath and Kern, 2003). This means detailed spatial configurations in offices need to be taken into account.

Both of these aspects, the almost complete lack of a systematic investigation of intra-organizational network structures as embedded within small scale spatial environments, as well as the lack of appreciation of detailed spatial configurations, shall be addressed by the empirical analysis presented in this paper.

The approach to construct and measure detailed spatial configurations that was used in this paper was based on Space Syntax modeling techniques, and as such will be explained in more detail in the following section on methods.

3. Methods and case studies

3.1. Constructing spatial configurations of a social network

Space Syntax is a theory and method concerned with the morphology of built form and the detailed configuration of spatial systems (Hillier, 1996; Hillier and Hanson, 1984). It originated in the 1970s from the attempt to understand whether there was an architectural or spatial explanation to the failure of 20th century English housing estates (Vaughan, 2008). Aiming at the investigation of the society–space relationship in general, and the relationship between space and organization as realized in complex buildings, Space Syntax analyzes the structure of spatial configuration, i.e. the way spatial elements are put together to form an interconnected network of spaces (for an introduction to Space Syntax also see: Bafna, 2003). The main proposition of Space Syntax research is that the character of social life within a space depends on the position of this space within the fabric of a city or a building: more integrated spaces (i.e. those with higher closeness centrality[1]) tend to be livelier and frequented by more people while more segregated spaces showed lesser frequentation. This general relationship between the collective flows of movement and the integrative capacity of a space is termed 'natural movement' (Hillier et al., 1993), and it is argued that spatial configuration influences movement flows in urban systems (Hillier and Iida, 2005) as well as in workplace environments (Sailer, 2007), which in turn affects the patterns of co-presence and encounter in space and thus the patterns of interaction between people.

The proposition that interactions between people are a by-product of movement flows and as such are influenced by spatial configuration renders Space Syntax an interesting method to bring to bear in the analysis of intra-organizational interaction networks. Furthermore, both social network analysis (Wasserman and Faust, 1994) and Space Syntax make use of graph theory in constructing a network: where a social network links agents (nodes) via ties (relationships between agents), the spatial network consists of nodes (streets in a city, rooms in a house, corridors in an office, etc.) and ties (intersections of streets or corridors, or doorways, passages and staircases in a house). One of the main modeling parameters in constructing a spatial network is the question of how to represent the continuous flow of space as a series of discrete and interconnected elements. In this paper axial and segment maps – as the most commonly used Space Syntax models – were used as spatial representations. An axial map in a workplace environment can be defined as the least set of all longest straight lines covering all parts of the building and minimizing depth or steps between spaces. In this scenario a line is no real entity, but a form of representing potential routes of movement; as such they are meaningful because they model the experience of agents in space. All potential routes of movement are covered from and to everyone's workstation, and all necessary links between lines are made to represent the relationship between people through space (for the original definition of axial maps in urban systems see: Hillier and Hanson, 1984, p. 91f.). This means, for example, that axial lines reaching from two adjacent offices A and B into a corridor do not connect directly, but via the corridor, to represent the fact that people located in A and B do need to cross the corridor to see each other. In essence, lines are connected where routes of movement intersect. A segment map, as described by Hillier and Iida (2005) is a refined version of an axial map, where every axial line is broken down into smaller segments at each intersection to provide a more fine grained analysis of spatial configuration. This means one long continuous axial line following the route through a corridor with n intersections will be broken down into $n+1$ segments. In both axial and segment maps, the connections between floors through staircases and elevators are also modeled to account for vertical distances. Since all routes are constructed along possible paths of movement, vertical connections are modeled based on the experience of agents and their movement patterns. In detail, this means that the line extending towards the elevator on one floor will be virtually connected with the line towards the elevator on the floors above or below, because this represents how people would move through space—going towards the elevator on one floor, entering the elevator and exiting on the floor above or below. Similarly, flights of staircases as well as landings are represented as lines and connected across the floors, as people would walk up and down.

In essence, axial and segment line maps define space as a linear sequence of possible paths through a continuous space based on the idea that movement flows are determined (at least partially) by configuration. This means lines and their connections are spatial representations of the social phenomenon of movement flows. Fig. 1 shows how an axial and segment map can be constructed as graphs using a sample floor plan.

In traditional Space Syntax analysis the constructed spatial graph would be used to calculate overall properties of each spatial element, for example its centrality. However, this paper is interested in distances between agents and therefore uses Space Syntax graphs to describe the quality or weight of routes between agents based on the detailed spatial configuration of the office building that houses the organization under investigation. In order to assign a location to an agent, a crucial assumption needs to be made, i.e. using the desk of a person as a proxy to their location within a building. Even though people obviously walk through offices during their working day and thus behave dynamically, assuming a fixed location in space for agents can be considered valid, since most work processes in knowledge-intensive work are still desk-based. Studies of offices across a variety of sectors show that people spend an average of 52% of their time at their desk (Alexi Marmot Associates, 2008). This was certainly true for the cases included in the analysis of this paper. Therefore desk location, or to be more precise, the centroid of the line leading to a desk, was used as proxy to the location of an agent in space.

The weight of a route from agent A to agent B, i.e. the cost of overcoming distance can then be described in terms of depth that is accumulated along a route of interconnected lines, starting from the line leading to the desk of A to the line leading to the desk of B, using the shortest spatial path through the network structure of existing lines. As introduced by Hillier and Iida (2005) and based on the SEGMEN model and software (Iida, 2009), four different ways of calculating depth were used:

1. Fewest steps in an *axial topology*, i.e. counting the minimum number of steps from a full line A to a full line B, where each

[1] Space Syntax uses a measurement called 'integration', which is comparable to closeness centrality. For details on the formula, its mathematical derivation and implications see Hillier and Hanson (1984, 108ff.).

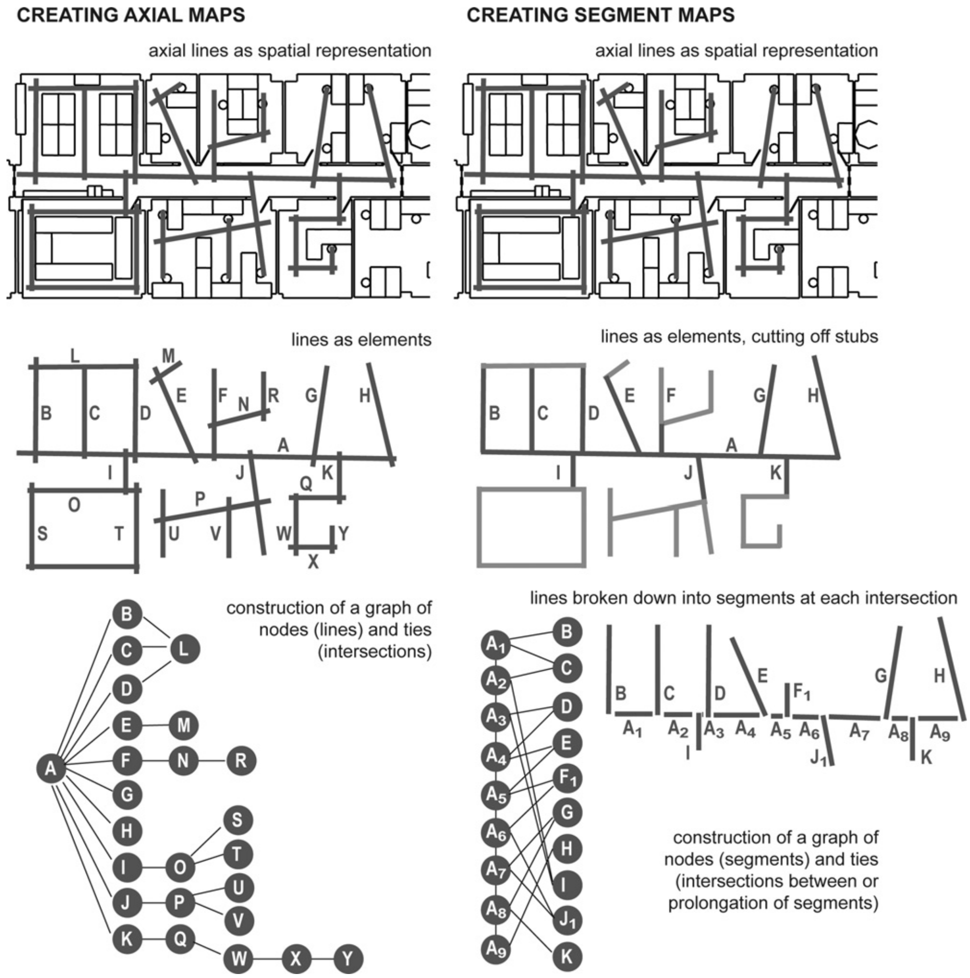

Fig. 1. Axial maps (left) and segment maps (right) as spatial representations to construct a network based on spatial configuration. Each map is based on the process of breaking down a complex space into discrete elements (lines of potential movement) and interconnecting them to represent a spatial layout as a graph structure.

different *line* involved counts as one step, excluding the root line (called 'axtopo' in the following).

2. Fewest steps in a *segment topology*, i.e. counting the minimum number of steps from segment A to segment B, where each different *segment* involved counts as one step, excluding the root segment (called 'topo' in the following).
3. Least length of path, i.e. shortest walking *distance in meters* from line A to line B along the path, as calculated from the center of each segment (called 'metric' in the following).
4. Least angle change, i.e. smallest accumulated totals of *angular change* on the route from line A to line B by assigning a weight to each intersection proportionate to the angle of incidence of two line segments at the intersection. The weight is defined so that the distance gain will be 1 when the turn is a right angle (called 'angular' in the following).

To test the importance of detailed configurations as described above, simple Euclidean distances between desk locations of agents were additionally calculated 'as the crow flies',[2] i.e. measuring the length of the direct shortest virtual line in 3D space based on *X*, *Y* and *Z* coordinates of desk locations (called 'Euclidean' in the following).

All different ways of calculating distances and depths between agents are shown in Fig. 2.

[2] 'As the crow flies' might be slightly misleading, because in this particular case of indoor spaces it means the crow would fly through walls and ceilings.

The different ways of measuring depth, i.e. distance costs for routes, all relate to aspects of how humans navigate through and make sense of environments. The measurement of walking distance in meters can be argued to be the actual cost of overcoming distance (Sailer, 2010), since it directly relates to the time and effort needed for agents to get together—twice the distance between agents means twice the time needed to overcome this distance, and therefore twice the distance cost for a route. An axial topology in contrast may represent perceived distances (Peponis et al., 2007), since two agents located at opposite ends of a very long corridor may find overcoming this distance relatively easy. Being located only two steps distance apart in an axial topology and therefore adjacent to the same axial line may feel as if the other person is 'just down the corridor' and hence relatively close, even though actual costs based on walking distance in meters could be relatively high (if the corridor is long enough). In essence, an axial topology can distort actual distance and therefore relates more to the experience and perception of agents than the straightforward effort-related measurement of walking distance. A segment topology can be argued to be a combination of the two: on the one hand it is based on the same logic as an axial topology and may therefore represent the perception of agents to a degree, since locations only a few segments away may be seen as close and locations many segments away as far, no matter how far away they actually are to walk; on the other hand, a segment topology can be highly correlated with walking distances, especially in cases where segments are roughly equal in length. Thus a segment topology may combine

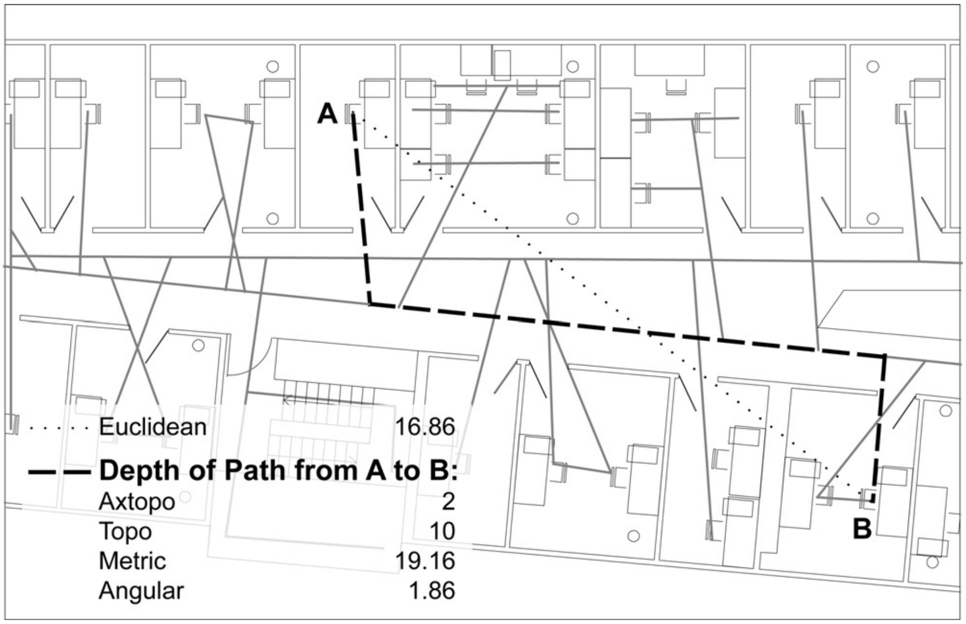

Fig. 2. The physical distance between the desks of agents A and B in an office layout can be modeled either as simple Euclidean distance, or based on Space Syntax as the number of steps in an axial topology along main routes of movement (shown as bold gray lines), the number of steps in a segment topology, path length in meters, and degree of angle change on the shortest route from A to B.

perceived and actual distance costs depending on its detailed configuration and network structure. Last but not least, angle changes can be argued to depict cognitive distances. Current studies of cognitive implications of spatial complexity suggest that the degree and frequency of angle changes shape human way-finding abilities and as such reflect how agents may navigate environments (Conroy Dalton, 2001, 2003). This means that routes with fewer angle changes are easier to remember and therefore may feel less costly to overcome due to their relative simplicity. Similarly to the perceived costs of an axial topology, angle changes may distort actual distances and will favor stretches of long straight or almost straight lines. Depending on the detailed configuration, the depth measurements of axial topology and angular change can be highly correlated. In summary, all four measurements of distance costs represent slightly different ways of describing the distance between locations, and the cognitive, perceived or actual costs involved to overcome those distances.

In order to integrate the various measurements of spatial depth and distance costs as a parameter in exponential random graph modeling, all paths between desk locations of agents were calculated based on all four different weighting methods and put into an adjacency matrix that used spatial depth as the strength of a tie. This way, detailed spatial configurations of paths between people were modeled as four different sets of networks to test the impact of physical space on social networks of interaction. This will be explained in greater detail in the section on exponential random graph modeling.

3.2. Case studies: intra-organizational interaction in knowledge-intensive organizations

Four different organizational data sets will be used in this paper for the empirical modeling (the same data sets were also used in: Sailer, 2010; Sailer and Penn, 2009). The organizations represent different knowledge-intensive work activities from the public and private sectors in the UK and Germany. The organizations were comparable regarding size (staff numbers ranged from 63 to 120), yet were located in contrasting spatial configurations.

In detail, the first two organizations in the data set were part of a UK university faculty. The same school was studied twice, once each in 2005 (69 staff) and 2008 (63 staff). The organization was spread over three different floors plus two additional small satellite offices in different buildings on campus; however, the majority of staff was placed on one floor. In between the two studies a small refurbishment of the office environment took place, which improved the look and feel of the space, but also changed some facilities of the mostly cellular office space. Additionally, organizational changes took place, such as new funded research projects and related staff turnover. This means that changing organizational structures embedded within an almost identical spatial configuration could be analyzed in this case.

The third organization, a research institute of theoretical physics in Germany, was studied in 2006. It occupied three floors of a newly built institute with mostly single and double cellular offices. The institute acted as a visitor's center, where researchers from all over the world came together for stays of up to 2 years to pursue their research interests. Two departments and several independent research groups with a total of 109 staff were studied in detail.

The fourth organization was a UK media company in the business-to-business publishing sector. It comprised 120 staff and occupied a four-storey building with mostly open plan environments.

While all four organizations were located in multi-storey buildings, the office accommodation varied, since the spaces of the university and research institute were mostly structured into single or double cellular offices as opposed to the open plan space of the media company.

All four organizations were studied over extended periods of time (2–8 weeks each); enquiring into work processes, organizational cultures and organizational characters by ethnographic observations and semi-structured in-depth and short interviews. Two social network data sets were gathered by online surveys: the frequency of interaction among all staff, rated on a 1–5 scale (5 = daily, 4 = several times a week, 3 = weekly, 2 = monthly, 1 = less often), as well as perceived levels of usefulness among staff (rated on a scale from 0 to 3 with 3 = very useful and 0 = not useful; in the case of the universities participants were asked to nominate useful contacts according to their contribution to teaching, research and support). The interaction data was dichotomized so that a link in the interaction network represents daily interaction only and this becomes the dependent network in the exponential random graph model presented in the next section. The usefulness data remained weighted in a matrix format and included as edge covariates in the modeling alongside the distance relationships.

3.3. Exponential random graph modeling procedures

Exponential random graph models (ergm) also known as p^* models are network probability models that account for dyadic dependence among a given set of nodes (Handcock et al., 2008; Robins et al., 1999; Wasserman and Pattison, 1996; Wasserman and Robins, 2007). The ergm is similar to logistic regression in that it estimates the presence of a binary dependent variable (in this case a link) conditioned on specified covariates. Given a w-vector of statistics, $g(Y,X)$ where Y is the dependent adjacency matrix and X is a covariate matrix, the ergm takes on the form:

$$P_\theta(Y = y|X) = \left(\frac{1}{k}\right)\exp\{\theta_{\mathrm{w}} g(y, X)\}$$

where k is a normalizing quantity to ensure a proper probability distribution and θ_{w} denotes the statistical parameters of the model. The covariate terms included in the ergm can be either network structural variables such as mutuality and transitivity or they can include covariates on both the nodes and the edges.

This paper investigates factors affecting the frequency of daily interaction among individuals in each of the four organizations. The dependent network is the directed, dichotomous network, where a link from node i to node j is present if node i reports daily interaction with node j. The goal of this study is to determine the importance of spatial considerations within the context of other social factors. Thus, our modeling approach first fits an ergm to the data using structural variables and organizationally relevant terms to create a base model. Then spatial variables are added to the base model in a second step.

The structural variables considered include edges, mutual links, and geometrically weighted edgewise shared partners (gwesp). A significant negative coefficient on the edges term can be interpreted as an actor cost associated with the effort to maintain a social link. The mutual links term indicates the level of reciprocity in the network. Significance in this term would show that both agents agreed in their perception of daily interaction frequency. The gwesp term (Morris et al., 2008) indicates how likely two agents will be connected based on linking to a common third node, similar to transitivity. The transitivity term can often lead to issues of degeneracy (Handcock, 2003a,b), which it does in these data. The gwesp term, however, presents a more intuitive social mechanism for network behavior. If two people have a friend in common, they are more likely to meet. If they have two friends in common, they are even more likely to meet. If, however, they have thirty friends in common and they have not met yet, there is probably a reason for it.

Hunter et al. (2008) have made it clear that failure to include second order dependency terms in network models can lead to bias in other model estimates. Since the purpose of ergm modeling in this application is not to estimate the structural properties of the network, but rather to estimate spatial effects while controlling for structural effects, it was deemed appropriate to include the structural variables as described above.

In order to control for alternate social mechanisms with a possible effect on interaction frequency three more terms were included in the ergm base models: firstly, self-reported usefulness, secondly, team affiliation of actors, and thirdly, the floor that actors work on.

Self-reported usefulness of other nodes was added as a link covariate. The usefulness covariate was described in the preceding section, where a directed, weighted link (0 = not useful; 3 = very useful) between node i and node j corresponds to node i's assessment of how useful he/she feels node j is to them. Usefulness is an important potential confounding factor that could affect daily interaction; previous studies have found highly significant correlations between the average frequency of interaction and cumulated self-reported usefulness of agents (Penn et al., 1999; Sailer and Penn, 2007). Therefore, it was deemed important to include in the model.

Team affiliation was modeled as dichotomous network (same team = 1, different team = 0) and added to the ergm as link covariate. Being members of the same team or research group could clearly affect interaction frequency, because close colleagues working on similar problems or tasks could be more likely to interact intensively with each other. In case 1 (University Faculty 2005) seven different research groups of varying group sizes (1–21 members) were distinguished; case 2 (University Faculty 2008) had five research groups (5–29 members), case 3 (Research Institute) had eight different research groups (1–43 members) and case 4 (Publisher) was made up of eleven different teams (1–29 members).

The floor that actors work on was similarly modeled as dichotomous network (same floor = 1, different floor = 0) and link covariate. Sharing the same office floor with colleagues could influence patterns of frequent interactions, as previous research has argued (Allen and Fustfeld, 1975), since people are normally reluctant to use elevators or stairs. Therefore agents on the same floor could be much more likely to interact frequently than those located on different floors.

Including the two variables of team affiliation and floor allows controlling for procedures of office assignments, i.e. the logic of how people are distributed in offices, which normally is far from being random. Generally, two different strategies can be distinguished: (1) a strategy of centralization and clustering of team members and (2) a strategy of distribution. The former would mean that those working on similar tasks and in the same group or team would sit in close proximity to each other, while the latter strategy would imply that people are scattered across space. The four organizations analyzed in this paper have employed diverse and combined strategies of office assignments (for a more detailed discussion see: Sailer, 2010): in cases 1 and 2 people were moderately distributed across the office, yet with localized clusters. Median walking distances from any group member to all others in the group ranged from 10 to 20 m for the smaller groups to over 80 m for the larger groups. This was due to shortage of office space and various additional factors that needed consideration in a university setting (status, rank, tasks, size of office, etc.). Case 3 showed a high degree of distribution with median distances of 55–101 m for group members to overcome, which means office allocation was almost random. Again, a general shortage of space was one reason for this, but also the visitors program of the Research Institute and thus the high fluctuation of staff contributed to distributed office allocations. In case 4 some tightly and some wide-spread teams could be found with median distances ranging from 7 to 54 m median walking distance among team members. Being a corporate organization the Publisher aimed at close proximities among team members, yet some people were clustered according to their function and not their team, for instance all web-related tasks were co-located and all editorial tasks were co-located, so that in effect the people working on the web and the editorial of the same team (i.e. magazine) were assigned desks in quite some distance apart.

Finally, five spatial models were developed adding different types of weighted distance between nodes (Euclidean distance, axial topology, segment topology, metric walking distance, angle change) as link covariates in the ergm to determine the statistical significance of space on link formation. In each case one spatial covariate was added to the base model containing the structural variables and additional covariates (usefulness, team, floor), since

Table 1
ergm models for 2005 University Faculty Network.

	M1	M2	M3	M4	M5	M6	M7	**M8**
Edges	−4.75	−4.78	−5.81	−4.97	−5.74	−4.97	−5.92	**−5.96**
Mutual	*Insig*	*Insig*	*Insig*	*Insig*	*Insig*	*Insig*	*Insig*	***Insig***
Gwesp	1.59	1.55	1.40	1.47	1.46	1.45	1.33	**1.29**
Usefulness		1.67	1.72			1.30		**1.39**
Team				1.07		0.95	1.04	**0.91**
Floor			1.66		1.60		1.58	**1.63**
AIC	879.79	858.54	844.83	839.64	838.36	830.93	807.63	**789.49**

Table 2
ergm for 2005 University Faculty Network.

	Control model					Spatial models				
Terms	Edges	Gwesp	Usefulness	Team	Floor	**Metric**	Angular change	Seg topo	Axial topo	Euclidean
Estimate	−5.9590	1.2925	1.3929	0.9123	1.6344	**−0.0584**	−0.1341	−0.1447	−0.0229	−0.0595
Std. error	0.0586	0.0251	0.1591	0.0521	0.0274	**0.0017**	0.5741	0.0204	0.0064	0.0014
p-value	≪0.0001	≪0.0001	≪0.0001	≪0.0001	≪0.0001	**≪0.0001**	≪0.0001	≪0.0001	0.0004	≪0.0001
AIC	789.49	789.49	789.49	789.49	789.49	**760.08**	793.66	780.7	819.28	780.2

there is a high degree of co-linearity between the spatial covariates. Statistically significant spatial covariates in the presence of other significant structural terms and socially relevant terms in a model can be interpreted as a significant effect of space on social interaction. Comparing the Akaike Information Criterion (AIC) for the base model (structural plus additional terms) with the AIC for the spatial model allows conclusions to be drawn about the role of spatial distance for interaction frequency. Moreover, it can be analyzed which of the five different spatial distance calculations models the data best, i.e. shows the lowest AIC value.

All ergm modeling was performed in R, using the statnet package version 2.2-1 (Handcock et al., 2009).

4. Results and discussion

The ergms were fitted to the four data sets as described in Section 3 above. The Monte Carlo maximum likelihood estimate of model parameters and significance values are reported for the base model including the perceived usefulness, team affiliation and floor covariates for each data set. The model parameters were stable in that the term estimates did not change much as additional terms such as usefulness, team, floor, or spatial covariates were added. Tables 1, 3, 5 and 7 compare various ergm models fit to the data using different combinations of terms with the structural terms always included. The models are arranged in the table such that the AIC improves to the right; blank cells were not included in the respective models. The model in bold with the lowest AIC is the model chosen as the base model. Tables 2, 4, 6 and 8 below present the detailed base model parameters for each data set on the left hand side, and the estimates of the five space covariates including the AIC on the right hand side. All spatial covariates are presented in one table per data set so that it is easier for the reader to compare and contrast the five approaches for modeling space as it affects social interaction. However, only one spatial covariate is included in each model. The spatial covariate with the lowest AIC value is marked in bold. The Markov Chain Monte Carlo standard errors are all less than 0.25% of the estimate for all ergms.

The results show a high degree of similarity in the ergms across the four data sets. The structural terms are significant for the majority of models and have similar coefficient values, highlighting the validity of the analysis. The negative coefficient on the edges term indicates that nodes are discouraged from making random links and that some form of utility drives their decision to interact with others. The positive coefficient on the mutual terms suggests that these networks exhibit reciprocity as expected. Two exceptions are worth mentioning: the mutual term is insignificant in the University Faculty 2005 case and shows a negative coefficient for the Publisher, which can only mean that the perception of agents regarding their interaction frequency was inconsistent. The significant gwesp term suggests that transitivity is a significant dynamic driving social interaction. However, in the case of the University Faculty 2008 gwesp was only significant when the perceived usefulness term was included. It can only be speculated why that is the case, although we might offer the possibility that in the university setting there may be an interaction effect where transitivity only exists among useful social links. Since the Faculty was very interdisciplinary and hosted specialized scientists working in distinct domains, it could well be the case that a common interest i.e. usefulness is necessary for transitivity to become a driver of frequent interaction. However, this would not explain the difference to the 2005 setting. Another possible explanation is that a kitchen and staff common room was provided for the organization in 2008 that was not available before. This not only increased overall levels of interaction, but could also have led to a higher degree of random encounters, decreasing the role of transitivity in non-useful interaction patterns.

The usefulness covariate is also significant in all data sets and the coefficient is positive. This indicates that agents are more likely to

Table 3
ergm models for 2008 University Faculty Network.

	M1	M2	M3	M4	M5	M6	M7	M8	**M9**
Edges	−3.66	−3.46	−3.69	−4.54	−4.82	−4.66	−4.84	−4.64	**−5.38**
Mutual	2.70	2.85	2.70	2.13	1.97	2.10	1.97	0.81	**0.52**
Gwesp	*Insig*			*Insig*	*Insig*			1.28	**1.04**
Usefulness		1.99	1.58			2.00	1.63	1.77	**1.41**
Team	0.86		0.63		0.83		0.59		**0.62**
Floor				2.15	2.11	2.14	2.12		**1.18**
AIC	1339.2	1325.3	1312.3	1232.8	1210.0	1194.4	1184.6	952.87	**915.18**

Table 4
ergm for 2008 University Faculty Network.

	Control model						Spatial models				
Terms	Edges	Mutual	Gwesp	Usefulness	Team	Floor	**Metric**	Angular change	Seg topo	Axial topo	Euclidean
Estimate	−5.3821	0.5204	1.0445	1.4111	0.618	1.1838	**−0.0117**	−0.0912	−0.0539	−0.0437	−0.0089
Std. error	0.0684	0.0334	0.0446	0.1655	0.0319	0.0096	**0.0069**	0.0211	0.0015	0.0005	0.0033
p-value	≪0.0001	≪0.0001	≪0.0001	≪0.0001	≪0.0001	≪0.0001	**≪0.0001**	≪0.0001	≪0.0001	≪0.0001	0.007
AIC	915.18	915.18	915.18	915.18	915.18	915.18	**864.79**	890.28	897.1	907.48	902.88

Table 5
ergm for Research Institute.

	M1	M2	M3	M4	M5	M6	**M7**
Edges	−4.82	−4.78	−4.77	−4.90	−4.98	−4.95	**−4.87**
Mutual	2.46	2.47	2.46	2.17	2.17	2.17	**2.17**
Gwesp	0.99	0.98	0.99	0.91	0.91	0.91	**0.91**
Usefulness				2.20	2.21	2.21	**2.21**
Team	0.16		0.16	0.13	0.13		
Floor	0.11	0.11			0.16	0.16	
AIC	2241.8	2240.5	2240.1	2073.1	2070.5	2070.0	**2067.7**

Table 6
ergm for Research Institute.

	Control model				Spatial models				
Terms	Edges	Mutual	Gwesp	Usefulness	**Metric**	Angular change	Seg topo	Axial topo	Euclidean
Estimate	−4.8674	2.1702	0.9085	2.2064	**−0.0156**	−0.1662	−0.0352	−0.1313	−0.0022
Std. error	0.0338	0.0798	0.0112	0.0773	**0.0007**	0.0036	0.0014	0.0027	0.0002
p-value	≪0.0001	≪0.0001	≪0.0001	≪0.0001	**≪0.0001**	≪0.0001	0.0001	≪0.0001	≪0.0001
AIC	2067.7	2067.7	2067.7	2067.7	**2010.1**	2064.2	2025.6	2035.6	2069.9

Table 7
ergm models for Publisher.

	M1	M2	M3	M4	M5	M6	M7	M8	**M9**
Edges	−4.89	−4.98	−4.98	−5.00	−5.00	−5.12	−5.14	−5.11	**−5.12**
Mutual		−1.16	−1.16	−1.16	−1.16	−1.20	−1.20	−1.20	**−1.20**
Gwesp	1.38	1.49	1.49	1.49	1.49	1.40	1.40	1.40	**1.40**
Usefulness						3.56	3.56	0.12	**3.55**
Team		*Insig*		*Insig*		−0.09		0.03	
Floor		−0.06	−0.06			0.05	0.05		
AIC	3693.2	3639.2	3637.6	3637.5	3635.4	3211.0	3210.0	3209.6	**3208.5**

have daily interaction with someone whom they perceive as useful to them.

The team covariates are significant in all data except the Research Institute. This means that generally agents tend to interact more frequently with colleagues belonging to the same research group or team. Interaction patterns in the Research Institute are obviously different from those in the other organizations, and the character and nature of this particular place offers a reasonable explanation. Scientists in this institute work on highly specialized research topics in theoretical physics, which are only shared by a handful of people around the world. Since the institute has a strong visitors program and has a high reputation in the field, the majority of scientists in this particular area would come to work at the institute at one point or another. This offers a unique opportunity for scientists to be at the same place with those working on the same problems at the same time, resulting in intensive interactions in micro-clusters, often in triplets. In contrast, some of the research groups are quite large and therefore contact among scientists is rather loose within the wider group. The team covariate is also not a strong predictor of frequent interaction in the case of the Publisher. The specific form of workflow in a matrix organization with multiple affiliations might offer an explanation here: staff at the Publisher are affiliated with a team (i.e. the magazine they produce), but they also share a disciplinary background with colleagues across teams, e.g. all sales people, or all editorial staff across the different magazines. Therefore frequent interactions are not necessarily bound by teams.

Table 8
ergm for 2008 Publisher.

	Control model				Spatial models				
Terms	Edges	Mutual	Gwesp	Usefulness	Metric	Angular change	Seg topo	**Axial topo**	Euclidean
Estimate	−5.121	−1.1975	1.4004	3.5533	−0.0283	−0.1665	−0.0547	**−0.1344**	−0.0032
Std. error	0.0712	0.0745	0.0211	0.1505	0.0003	0.0017	0.0006	**0.0015**	0.0012
p-value	≪0.0001	≪0.0001	≪0.0001	≪0.0001	≪0.0001	≪0.0001	0.0001	**≪0.0001**	≪0.0001
AIC	3208.50	3208.50	3208.50	3208.50	3089.3	3078.1	3063.4	**3059.4**	3205.4

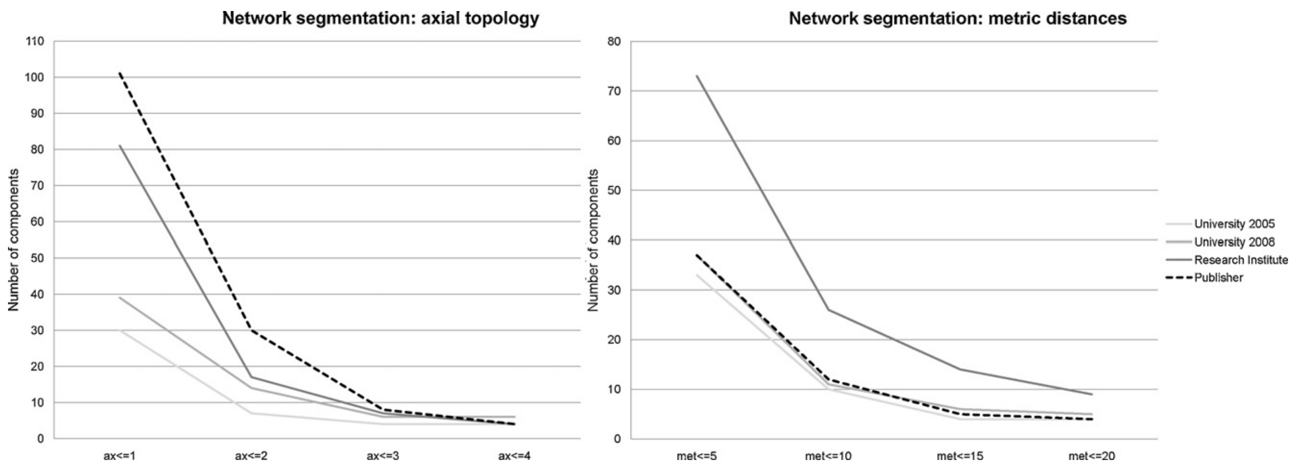

Fig. 3. Analysis of network segmentation, i.e. the number of components in the network dependent on a stepwise increase of physical distance for the number of steps in an axial topology (left) and metric distance (right).

The floor covariates are significant in all data sets and show mostly positive coefficients. This means that agents tend to interact more frequently with those located on the same floor. This is especially the case for the two University settings. In the cases of the Research Institute and the Publisher, the floor covariate does not necessarily improve the AIC of the model—similar to the team covariate in both cases, and very likely for similar reasons, i.e. specialism (Research Institute) and multiple affiliations (Publisher) and the respective office allocation strategies described in Section 3.3. This means that team affiliation and floor, while significant, did not provide additional explanatory power in all of the models. Thus, the team and floor covariates are included in the 2005 and 2008 university faculty data, yet they are omitted from the research institute and the publisher data.

In all cases, the best model with the lowest AIC is presented as the base model in order to demonstrate the impact of space on social interaction: if detailed spatial configuration matters, we would expect the models including spatial covariates to show an even lower AIC value than the best model without detailed spatial information.

The results show that the spatial covariates were significant factors on social interaction with a p-value less than 0.0001 in the majority of models and cases. Including spatial covariates resulted in a better fit of all models with lower AIC values across all cases. This is even the case for the university setting, where the majority of staff is located on one floor. This indicates that space does contribute significantly to social interaction. All five methods of calculating distance are generally significant, so the AIC provides an estimate of the quality of the model. In the majority of cases Euclidean distance results in the highest AIC values, which means it does not model the data as well as the Space Syntax related measurements. The results confirm the assumptions made in this paper that detailed spatial configurations matter in the modeling of small scale environments. The way Euclidean distances draw direct lines between agents regardless of ceilings and walls does not truly reflect the placement of agents and their social relations in space. Since Euclidean distance is highly correlated with the other distance metrics, it could be argued that it matters only insofar as it provides a proxy for more meaningful spatial measures. In three cases (University 2005 and 2008, Research Institute) walking distance in meters provides the best model. For the fourth data set, however, axial topology provided a better explanation of social interaction than the other three Space Syntax approaches or Euclidean distance. It is interesting to note that the Publisher is the only organization that inhabits an open plan office, whereas the other three organizations occupy mostly enclosed and cellular office structures.

So how exactly does the layout of an office matter, or to be more precise, how do office typologies create distinct spatial configurations, which then in turn unfold effects on interaction patterns?

This relationship between office typology (cellular versus open plan) and spatial configuration (walking distance in meters versus axial topology) can be further investigated by systematically looking at spatial network structures and clustering behaviors for different distance thresholds. For this analysis, axial step depth i.e. the number of steps taken in an axial topology was used as a threshold, so the research investigated, which agents were 1, 2, 3 or 4 steps away from each other and only those closer than 1, 2, 3 or 4 steps were linked to each other in four different network visualizations. Then the number of separate components were counted and plotted as a diagram in Fig. 3 (left). The same procedure was repeated for walking distances of 5, 10, 15, and 20 m, representing close proximity relationships and the resulting analysis is shown in Fig. 3 (right). The results highlight the differences between the Publisher and the other three organizations: few axial steps lead to the highest number of components for the Publisher ($n = 101$), yet the number of components drops steeply as axial steps rise to 2, 3 and 4. This means that in very close perceived proximity, i.e. those reachable in one step, lots of small clusters dominate the network structure of the Publisher. This effect is created by the open-plan office layout of the organization, which mainly consists of bays of desks (see Fig. 4a). In order to walk from agent A to B, only short metric distances are required, yet the routes involve relatively high numbers of axial lines compared to the other cases. Axial topology therefore is a measurement that is highly discriminating in the case of this organization, but not necessarily for the other organizations, as Fig. 3 shows.

Walking distance in meters, as illustrated in the right graph in Fig. 3 is a measurement that is discriminating for all organizations, since the drop rate is comparable across the sample. However, the organization in which walking distances mattered most was the Research Institute, which was spatially organized as two floors of cellular office accommodation along three long corridors meeting in the center of the building (see Fig. 4b). This structure made walking distances very long, yet perceived distances as measured in axial steps were rather short; high clustering already showed within two steps of reach.

In essence, it can be argued that the detailed difference in office layouts results in distinct morphologies of spatial configuration, which in turn have an effect on tie formation in interaction net-

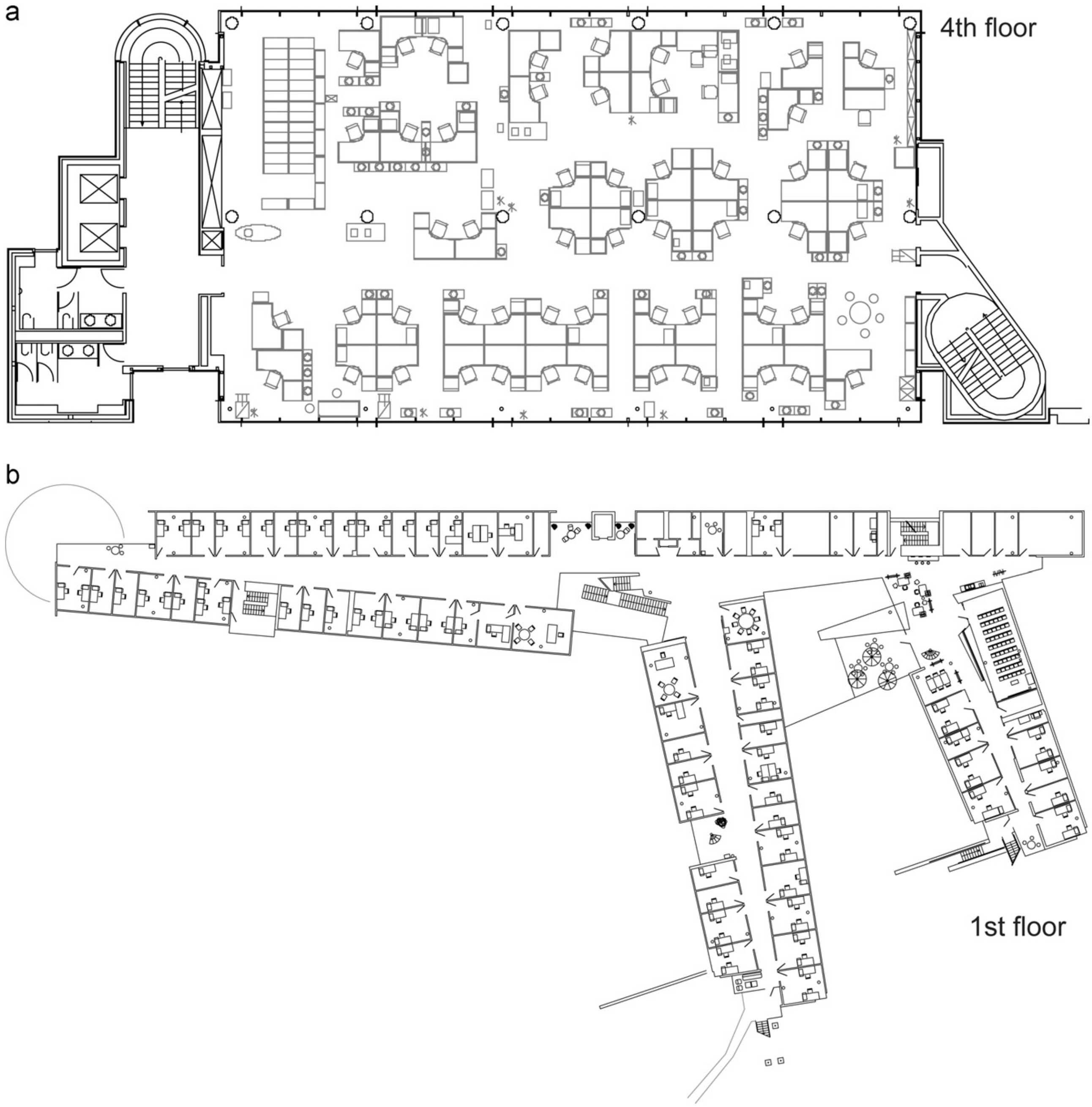

Fig. 4. (a) Floor plan of a sample floor of the Publisher (open-plan office); (b) floor plan of a sample floor of the Research Institute (cellular office).

works as shown in the ergm. While a cellular accommodation with aggregated cells in long stretched corridors creates perceived closeness and actual distance, an open plan office layout generates structures of perceived distance and actual closeness.

5. Conclusion

This paper has investigated various notions of distance among actors within knowledge-intensive office-based organizations and the consequences of these distances for the formation of network structures. Based on research in the field of Space Syntax, the paper showed that distance can be measured in five different ways—the number of steps in an axial line topology, the number of steps in a more refined segment topology, path length in meters and the degree of angle change, in addition to the measure of simple Euclidean distance. It was argued that the Space Syntax derived measurements reflect the cognitive and perceived distances among actors (axial topology, angle change), actual distances to be overcome (walking distance), as well as a combination of the two (segment topology). In order to find which factors contributed to daily interaction among agents, this paper constructed spatial networks and used each distance measure as edge covariates in an exponential random graph modeling approach for daily interaction, alongside structural network measures such as reciprocity or transitivity, and organizational measurements such as the perception of usefulness among agents, team affiliation and office allocations on different floors.

Several contributions to the study of social networks have been provided. By bringing together two related fields (Space Syntax and social network analysis) that are still underexplored in their interplay, we were able to show that the likelihood of two people interacting not only depended on structural effects within networks, such as reciprocity and transitivity, or organizational effects, such as perceived usefulness among actors or team affiliation, but also on the physical distance separating actors. Euclidean distances in small scale environments were significant, yet not as powerful in modeling social interaction. This means that Space Syntax distance measures can be considered a significant indicator of network structures of interaction, while controlling for other factors. While this is an interesting finding in itself, more detail was added by investigating which spatial measure resulted in the best fit. Metric distance was the most successful measure in three cases, while axial topology was more effective in one case. It was argued that this could have been caused by the detailed spatial configuration of the office layout: cellular office arrangements seemed to create spatial networks of perceived closeness and actual distance, whereas the studied open-plan arrangement resulted in perceived distance and actual closeness. This underlines the importance of analyzing detailed spatial configurations, and understanding the impact of small-scale design decisions.

Various limitations of this study need to be considered. The common problem of missing data and low response rates could potentially have biased the results. Return rates varied from 65% (University 2005), 73% (University 2008), 84% (Research Institute) and 40% (Publisher). This means that the deviating pattern in the case of the Publishing Organization, where the number of steps seemed to shape network structures to a higher degree than walking distance could have been caused by missing data rather than a different office configuration. Recent arguments have highlighted that certain network measurements and types of analysis are more robust than others, when it comes to missing data (Everett, 2009); specifically, it was argued that an ergm can still result in consistent estimates of structural effects even with a sizeable proportion of non-respondents (Robins et al., 2004). Still, the proposition that detailed configurations in the office layout may be responsible for creating distinct closeness and distance patterns and as such have an effect on network structures of interaction requires further research and a more systematic investigation of open-plan and cellular office environments. Also, the data may suffer from the common problem of a research design based on self-reports, since it only depicts the perception of agents and not necessarily actual interaction patterns. What is more, the ergm analysis reported in this paper was restricted to a limited number of structural terms; in future research additional and more detailed nodal attributes could be considered to account for the well-reported effects of homophily on network structures.

Last but not least, future research could investigate the mechanisms of how space works in greater detail. Does space create an opportunity for interaction due to proximity, in essence creating a propinquity effect, as argued by Festinger et al. (1950), or does space create a hindrance to interaction due to distance, as argued for example by Allen and Fustfeld (1975)? Or does space act as 'a field of probabilistic encounter', as argued by Hillier et al. (1987)? Further research could shed light on these questions by interviewing subjects and analyzing reasons for frequent and non-frequent interactions more closely, as well as distinguishing types of interactions (work-related, social, information exchange, etc.) and types of layout in turn. Furthermore, organizational purpose may come into play and may form an interesting factor to consider, i.e. do spatial distances make a difference for organizations with a common purpose and goal (e.g. most corporations) and is this similar to those organizations with more individualistic purposes (e.g. universities or research institutes)?

By showing how the various concepts of spatial distance provided a fruitful context for the study of network structures in graph modeling, and how spatial configuration can be studied in detail with the help of Space Syntax methodologies, this paper has laid a foundation for future research on the relationship between social networks and spatial analysis methods.

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