

## Research Article

# Functional and Social Team Dynamics in Industrial Settings

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Like other social systems, corporations comprise networks of individuals that share information and create interdependencies among their actions. The properties of these networks are crucial to a corporation's success. Understanding how individuals self-organize into teams and how this relates to performance is a challenge for managers and management software developers looking for ways to enhance corporate tasks. In this paper, we analyze functional and social communication networks from industrial production plants and relate their properties to performance. We use internal management software data that reveal aspects of functional and social communications among workers. We found that distinct features of functional and social communication networks emerge. The former are asymmetrical, and the latter are segregated by job title, i.e., executives, managers, supervisors, and operators. We show that performance is negatively correlated with the volume of functional communications but positively correlated with the density of the emerging communication networks. Exposing social dynamics in the workplace matters given the increasing digitization and automation of corporate tasks and managerial processes.

## 1. Introduction

Corporations are complex systems comprising dynamic social networks where information flows across organizational structures [1–5]. People organize their activities in corporations such that collective goals can be achieved. Communication is key for establishing interdependencies among individual actions, which include the assignment of tasks from managers to workers, reports from workers to managers, and cross communication in informal settings [2]. The way people choose to communicate and the information they share influence the structure of the emerging social networks [6]. Visualizing and analyzing the structure of these networks is crucial for understanding the functioning of the social system and intervening to foster efficient behaviors [7, 8].

The introduction of automation and software to organize and conduct corporate work creates the opportunity to observe and characterize the structure of corporations' social networks through data [6]. By using software to assign work

orders, schedule meetings, and exchange messages, users leave traces in data that reveal the corporation's patterns of self-organization [9–11]. Corporations comprise teams, and teams comprise individuals. Understanding how individuals aggregate into teams, and how teams form corporations, is essential to maintaining cohesion and improving performance at scale [12–14].

Corporations can become more complex either because they grow in size or in the variety of services they supply [15, 16]. In this process, their substructure becomes more important to their performance [5, 13, 17]. According to Ashby's law of requisite variety, systems must match the complexity of their environment in order to be successful [18, 19]. By coalescing into teams, assuming specialized roles, and creating interdependencies among each other, individuals gain collective capabilities that exceed their own and can respond to the increasing demands [20]. The complementary array of behaviors that emerge from individuals associating into teams is key for building effective corporations [21].

Fundamentally, teams are groups of people that work together and communicate with each other. Communication is the basis for creating and maintaining trust and satisfaction among team members [22]. Team communication falls into two overarching categories: functional and social communications [2, 4, 8, 23]. Functional communications, such as task lists and scheduled meetings, are how work is officially organized and done [2]. Social communications, such as chatting online, act as a kind of scaffold for functional communication by igniting and fortifying social relations and the benefits associated with them for the individual and the group [24]. While they are not intentionally planned, they are essential to a well-functioning corporation. Understanding the function and interplay of these two channels of communication is essential to understanding what makes a team cohesive and more productive [2, 4, 5, 12].

In this paper, we analyze data from a management software company in industrial settings and construct and characterize their functional and social communication networks. We characterize users and teams by their individual and collective behaviors, namely, how they organize work (functional communications) and chat with each other on the software platform (social communications). We identify patterns of the network structure, such as asymmetries and lateral communications, and analyze patterns that improve or degrade team efficacy.

We show that functional networks are asymmetrical and social communication networks are segregated by role or job title. We can observe the difference in behavior in Figure 1. Companies are shown by two dots representing functional (blue) and social (orange) communication networks. The  $x$ -axis represents degree assortativity, and the  $y$ -axis represents job-title assortativity (see Sections 4 and 5 for more details). Negative degree assortativity indicates asymmetry of interactions, and positive job-title assortativity indicates segregation by role. In the majority of cases, the two types of networks are clearly in separate regions of the space.

This paper is organized as follows: In Section 2, we discuss the related work. In Section 3, we discuss the dataset we analyzed. In Section 4, we explain how we construct functional and social networks and show their properties. In Section 5, we compare the structure of both networks, and in Section 6, we compare their dynamical behavior. In Section 7, we analyze their relationship to efficacy. Finally, in Section 8, we present our conclusions.

## 2. Related Works

The literature on the implications of functional and social communication patterns on team performance includes many types of corporations and areas. Some studies propose that functional communication is related to productivity [25], while others report that managers disregard formal contacts to a surprising extent [4]. The rise in complexity has been shown to be related to a decline in hierarchical structures [21]. However, other studies claim that hierarchies persist [5]. Social communications have also been

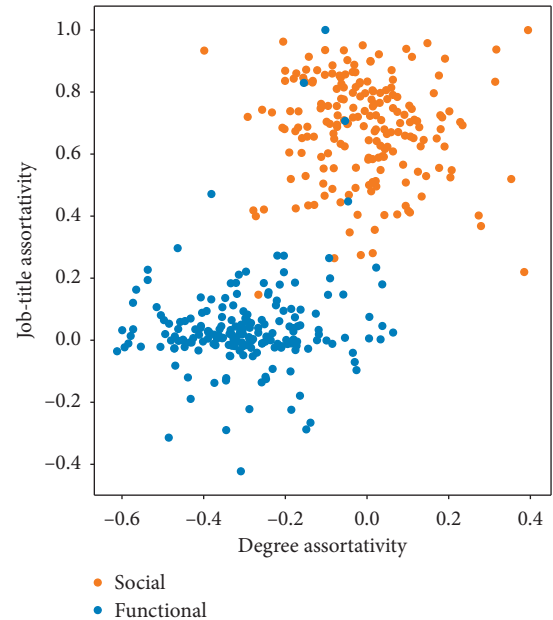


FIGURE 1: Degree and job-title assortativity coefficients of functional and social communication networks for all enterprises. Each company is shown by two dots representing functional (blue) and social (orange) communication networks. Negative degree assortativity indicates asymmetry of interactions, and positive job-title assortativity indicates segregation by role.

analyzed in work settings. They may replace formal communication in the context of uncertainty [26]. The cohesion of face-to-face social networks has been positively associated with higher worker productivity, while the opposite is true in email communication [27]. In other settings, social ties have been observed vertically [4]. The information provided by formal communications might ease managers' activities, while employees might prefer to communicate informally [25].

The analysis of team dynamics and performance has been relevant in multiple contexts, including work settings [28], international organizations [29], military [30], sports [31], and gaming [32]. These studies show that team performance depends on communication among members and other teams [33–37]. Either within or across teams, the networked structure of both formal and informal social relationships can improve information flows, facilitate the coordination of activities, and result in better performance [28]. The more evenly the team members communicate with each other, the better the teams seem to perform [38]. A more recent study using electronic badges to measure interpersonal communication across startups found that the amount of communication correlates with better performance, though too much communication with other teams seems to be detrimental [39].

These studies either are qualitative or lack the detailed, fine-grained interaction data as the one we analyze in this paper. For example, while sensors may reveal offline communication patterns, the data collected from such methods cannot differentiate between formal and informal

communications. Understanding the role of these two different types of interactions regarding team performance is crucial for creating the right environmental conditions for workers to develop their activities. Moreover, previous studies generally lack the opportunity to observe multiple companies together and usually include single case studies, which limits the possibility to generalize results.

### 3. Data

We analyze anonymized communication data from a management software platform that organizes work in industrial settings. The software integrates in a single platform both the assignment of work orders, which we define as functional communications, and social interactions among workers and team members in the form of online chats. These online chats are generally used by workers to informally coordinate their activities during work hours. In total, we analyze the behavior of 38,137 distinct users from 197 factories over a period of five years (2013–2018). The distribution of factories' life-span in the platform is shown in Supplementary Materials (Section S1). Interactions include work-order assignment for functional communications and chats for social communications. Work orders have a creator and a target. Chats occur as a sequence of messages populated freely by workers and team members.

### 4. Functional and Social Communication Networks

We first analyze the structure of functional communication networks by extracting the assignment of work orders from each enterprise's historical data. We create one network for each enterprise. Nodes represent users, and edges represent work-order assignments. Edges are directed from the work-order creator to the assigned user and weighted by the total number of interactions between each pair of users. Figure 2 shows network visualizations of select enterprises' functional communication networks (other enterprises are shown in Section S2). Users have been colored by their job title: executives in red, managers in dark blue, supervisors in orange, and operators in light blue.

Functional communication networks are characterized by a hub-spoke structure, which consists of a dense core of users assigning work orders out to users in a radial periphery. The core users are generally higher ranked than the peripheral users. While the former distribute orders among core and peripheral users, the latter seem to only communicate with their superiors.

An alternative method for visualizing a network's interaction patterns is the adjacency matrix. Adjacency matrices show the interactions between any pair of users organized in rows and columns. Figure 3 shows adjacency matrices of the select enterprises' functional communication networks presented in Figure 2. Users have been sorted by their job title and their number of work-order assignments. Row users are sending work orders, while column users are receiving them. The color (from white to black) is

proportional to the log value of the number of interactions between any pair of users. These adjacency matrices are characterized by their sparsity and streaking horizontal lines, which indicate most users are not assigning work orders, but receiving them. This pattern is consistent with the hub-spoke structure in Figure 2. Core users appear as horizontal streaks, while peripheral users account for the matrices' sparsity. Moreover, core users' horizontal streaks slice through all job titles.

A user's interaction pattern indicates their role in the enterprise. Figure 4 shows in-degree vs out-degree scatter plots of select enterprises' functional communication networks. Dots represent users, and colors are consistent with their job titles. In-degree ( $x$ -axis) measures the number of work orders a user receives, and out-degree ( $y$ -axis) measures the number of work orders a user assigns. Users above the diagonal assign more work orders than they receive. These users have leading roles and appear central in the network visualizations shown in Figure 2. Users below the diagonal receive more work orders than they assign and, in the same figure, appear peripheral. In general, there are more users below the diagonal than above it, which shows that a few leaders account for most workers' work orders. In some cases, such as panels (a) and (i), a clear distinction between job titles or roles in teams manifests.

In order to analyze social communication networks, we extract the exchange of messages from each enterprise's historical chat data. These chats take place within the management software platform and create the space for workers and team members to interact and exchange information about their ongoing activities and work orders. We create one network for each enterprise. Nodes represent users, and edges represent exchanged messages. Edges are directed from the message sender to the recipient and weighted by the total number of exchanges between each pair of users. Figure 5 shows network visualizations for the select enterprises' social communication networks. Other enterprises are shown in Section S2. Users have been colored by their job title: executives in red, managers in dark blue, supervisors in orange, and operators in light blue.

Social communication networks are characterized by groups. For example, in Figures 5(b), 5(c), and 5(g), a clear preference of users to interact with those with a similar job title manifests, specifically in managers with managers and operators with operators. We visualize the group structure of these networks with their adjacency matrices in a fashion similar to that in Figure 3, but here we sort users based on the agglomerative clusters they create as they interact. Figure 6 shows the clustered adjacency matrices of the select enterprises' social communication networks presented in Figure 5. The number of clusters generally corresponds to the groups observed in the networks of Figure 5. In panels (a), (b), and (c), clusters are clearly visible in both the network and the matrices. In some cases, the matrices reveal groups that are not apparent (e.g., panel (f)). This result contrasts the previous study [4], which states social ties are more likely to be made vertically than horizontally.

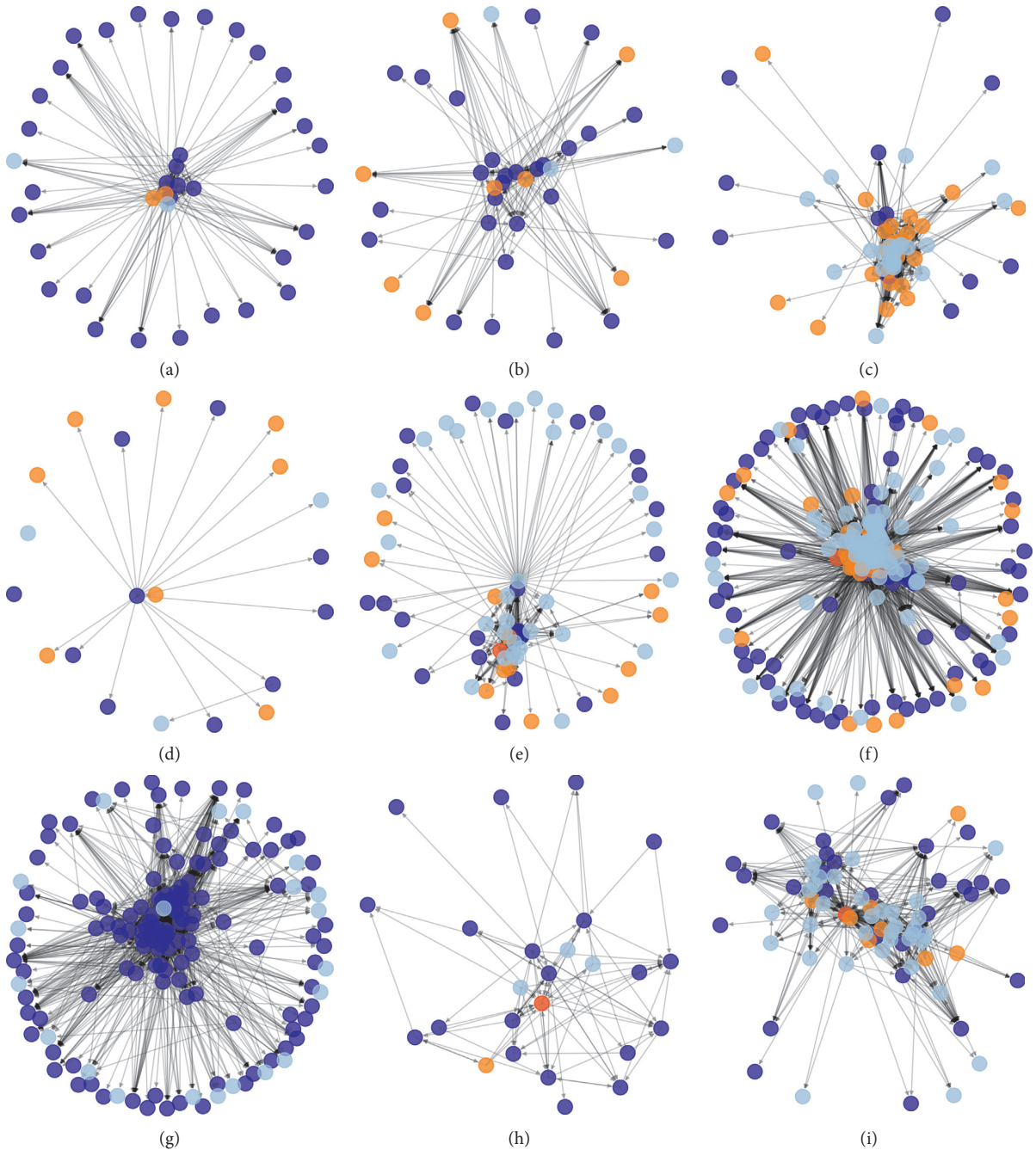


FIGURE 2: Visualization of functional communication networks from select enterprises. Distinct networks represent different enterprises. Nodes are user colored by their role (red is for an executive, dark blue is for a manager, orange is for a supervisor, and light blue is for an operator). Directed edges are work orders. Networks have a hub-spoke shape, consisting of a middle core and a radial periphery. Nodes were positioned using the Fruchterman–Reingold force-directed algorithm [40]. Other enterprises are shown in Section S2.

## 5. Comparing Functional and Social Communication Networks

We compare functional and social communication networks by analyzing multiple network features. These features summarize the network structure as scalar values we can use to compare types of communications within and across companies. Specifically, we study the following network properties: the number of nodes (users), number of edges

(communications), density, average clustering coefficient, inequality in connections (measured via the Gini coefficient of the degree distribution), and assortativity by degree and job title. We calculate these metrics for each network and analyze their distribution across all enterprises. The results are presented in Figure 7, and a set of statistical tests is shown in Table 1.

We measure the density of the network as the relative number of existing edges with respect to all those possible.

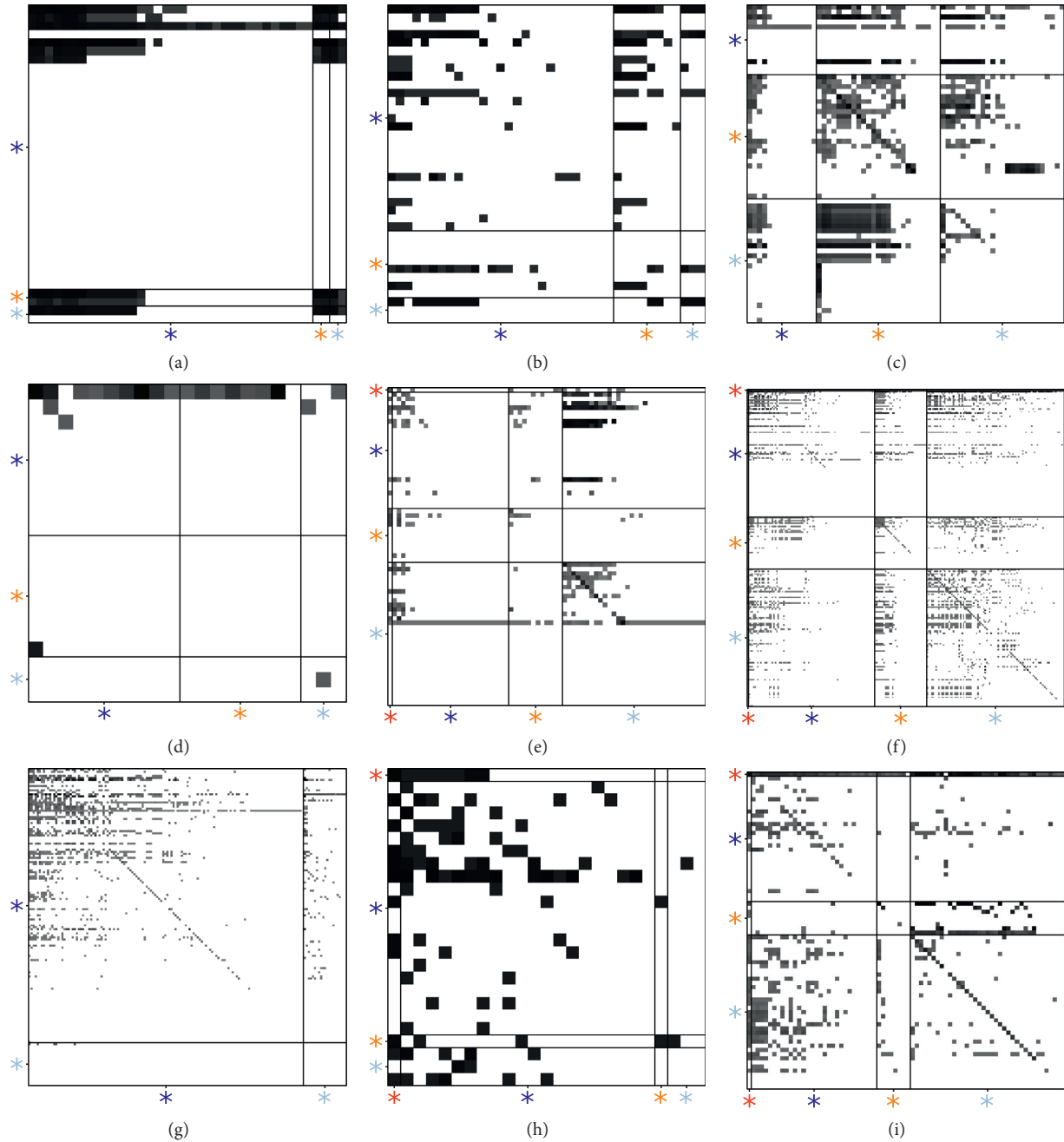


FIGURE 3: Adjacency matrices of functional communication networks from select enterprises. Color intensity indicates the log value of the weighted number of edges. Horizontal and vertical lines divide matrices into labeled, role-specific sections (red is for an executive, dark blue is for a manager, orange is for a supervisor, and light blue is for an operator). Diagonal squares are areas of intrarole communication, and others are areas of interrole communication. Adjacency matrices are sparse and distinguished by their streaking horizontal lines. Other enterprises are shown in Section S2.

Density values lie between 0 and 1 and show how dense or sparse networks are. The networks emerging from social communications seem to be denser than the ones arising from functional interactions (Figure 7(c)). This is consistent with the network visualizations and matrices shown in Figures 2–6. The radial topology of functional networks creates a less dense structure than the clustered groups of social communications. Correspondingly, the average clustering coefficient in social communication

networks is higher than that in functional ones (Figure 7(d)). The clustering coefficient counts the relative number of triangular connections with respect to all those possible. It also goes from 0 to 1 and shows that functional networks are less cohesively connected than social communications.

Functional networks are more centralized. We measure centralization via the Gini coefficient of the degree distribution for all networks (Figure 7(e)). The Gini coefficient of the degree distribution quantifies the unequal concentration

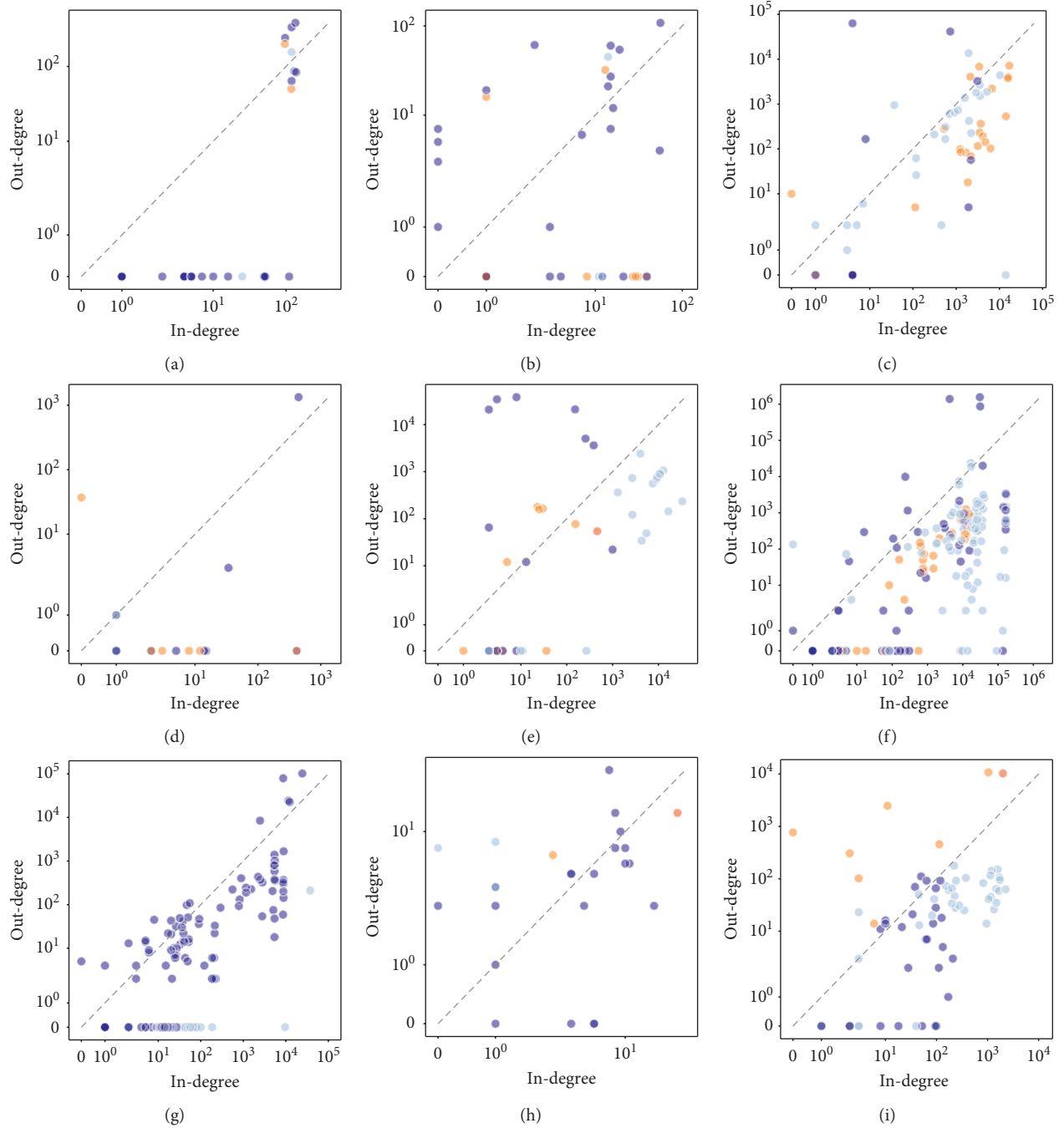


FIGURE 4: In-degree vs out-degree scatter plots of functional communication networks from select enterprises. Dots are user colored by their role (red is for an executive, dark blue is for a manager, orange is for a supervisor, and light blue is for an operator). Dots above the diagonal are users that assign more work orders than they receive. Dots below the diagonal are users that receive more work orders than they assign. Dots near the diagonal are users that assign approximately as many work orders as they receive.

of edges among highly connected nodes. It also ranges between 0 and 1, with 0 being the case where connections are equally distributed among all nodes and 1 being the case where the most connected node gathers all possible connections. This metric is often used to estimate income inequality. In this case, the Gini coefficient of functional networks is consistently higher than the one from social communications, which suggests that functional networks seem to be more hierarchical.

We also analyze mixing patterns such as an asymmetrical structure and preference of users to segregate interactions based on job title. We quantify such mixing patterns using assortativity [43], which measures the tendency of nodes to be connected to those that are similar. For an asymmetrical structure, we measure the tendency of nodes to be connected based on their degree. For segregation, we measure the tendency of nodes to be connected based on their job title.

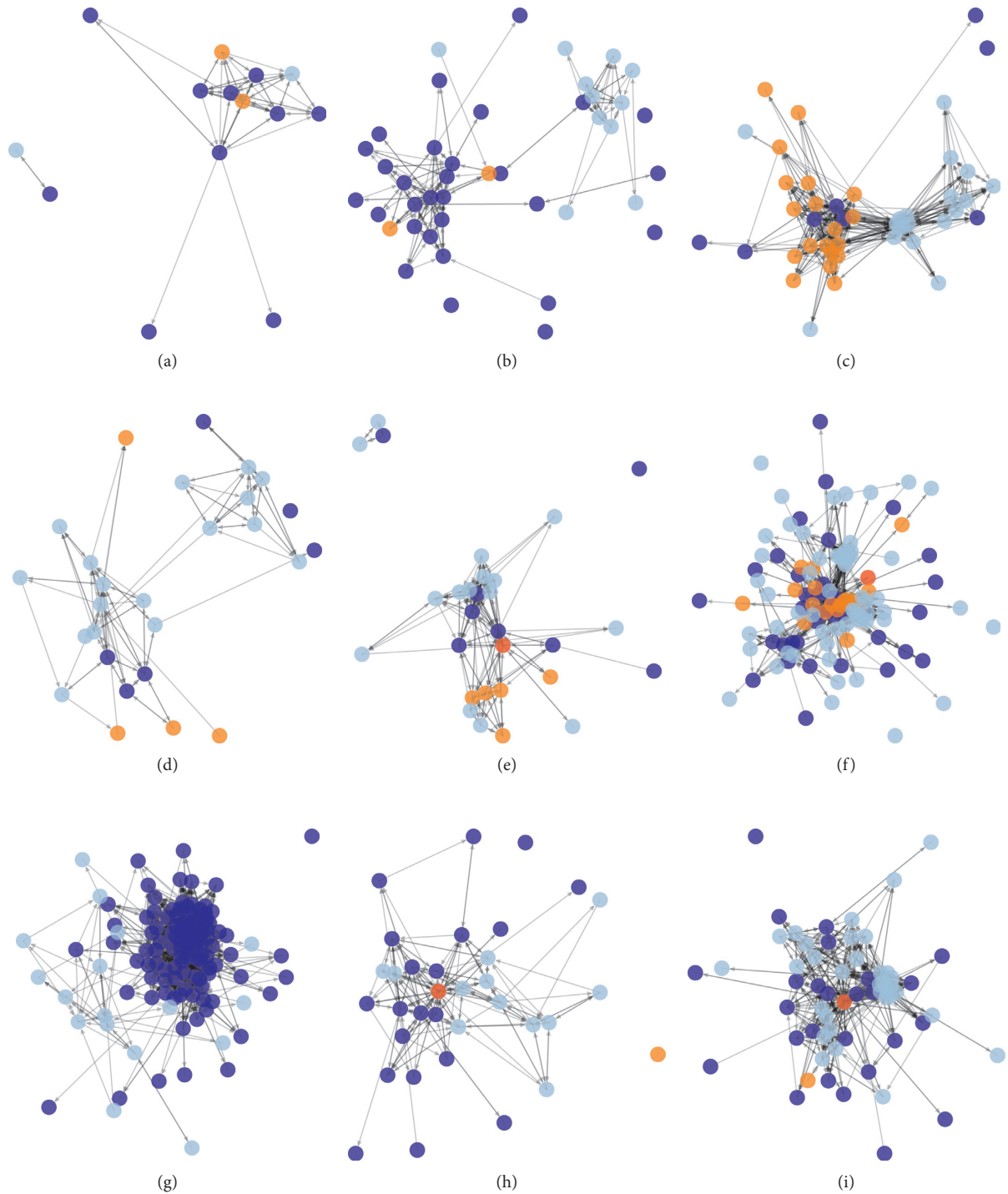


FIGURE 5: Visualization of social communication networks from select enterprises. Distinct networks represent different enterprises. Nodes are user colored by their role (red is for an executive, dark blue is for a manager, orange is for a supervisor, and light blue is for an operator). Edges are directed and represent messages in online chats. Other enterprises are shown in Section S2.

Assortativity by degree measures the similarity of connections in the network with respect to node degree by calculating the Pearson correlation of degrees at each end of the edges. Positive assortativity means that nodes are linked to those with a similar degree of connectivity. Negative assortativity indicates that highly connected nodes are linked to poorly connected ones. If the correlation is zero, it

indicates that connections are drawn independently. In Figure 7(f), we show the histogram of the assortativity by degree coefficient of all enterprises and both types of communication networks (blue for functional and orange for social). Functional communication networks have a negative assortativity by degree, while social ones have no correlation. This shows that functional communication

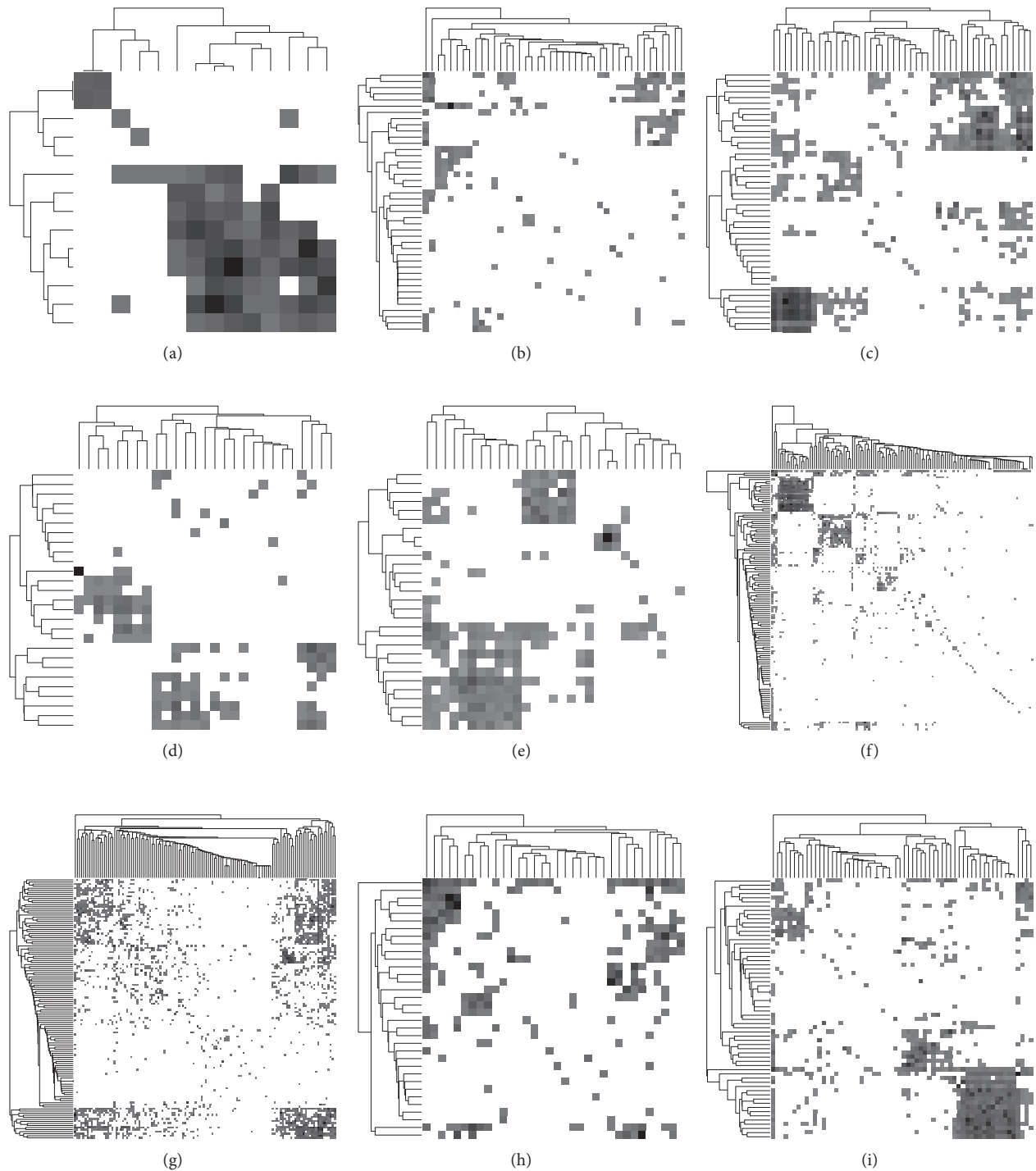


FIGURE 6: Clustered adjacency matrices of social communication networks from select enterprises. Color intensity indicates the log value of the number of weighted edges. Nodes are sorted using an agglomerative clustering algorithm [41, 42]. The dendrogram representing the sorting results is shown together with its respective matrices.

networks are more asymmetrical than social ones. This is related to the hub-spoke structure in Figure 2 and reflects the organization of leadership in the enterprise. Previous work shows that networks of acquaintances, sexual interactions, and celebrities generally show positive assortativity by degree [43], which demonstrates that the functional communication networks in enterprises are not behaving like regular social networks. Moreover, it has been reported that

asymmetrical communication structures persist in organizations, especially in more traditional ones [5].

We measure the segregation of interactions by job title using assortativity by attribute (the attribute being job title). Positive values show segregation of interactions by job title, while zero shows no correlation. In Figure 7(g), we show that social networks (orange) are much more segregated by job title than functional networks, where



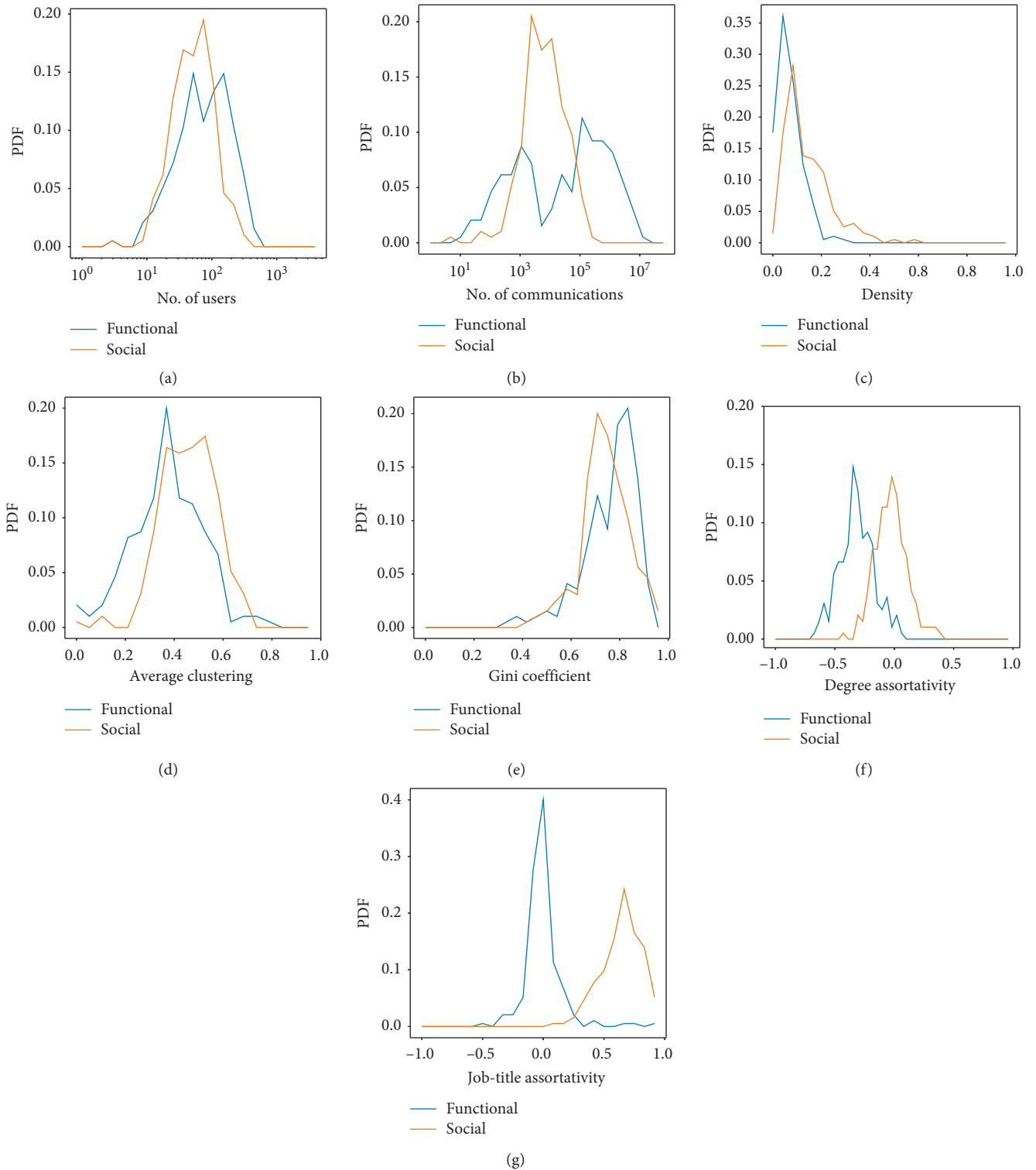


FIGURE 7: Properties of functional (blue) and social (orange) communication networks for all enterprises. (a) Distributions of a number of users. (b) Distributions of a number of communications. (c) Distribution network density. (d) Distribution of average clustering. (e) Distribution of Gini coefficients of the degree distributions. (f) Distribution of degree assortativity coefficients. Negative values indicate asymmetrical interactions. (g) Distribution of job-title assortativity coefficients. Positive values indicate segregated interactions. A set of statistical tests comparing these distributions is shown in Table 1.

work orders are assigned across different types of employees. This is consistent with the horizontal streaks present in the matrices of Figure 3.

We estimate the significance of the differences among distributions arising from functional and social communication networks by performing a set of statistical tests on each

TABLE 1: Statistical tests comparing the distributions of network features from functional and social communication networks. The Kolmogorov–Smirnov (KS) test measures whether samples come from the same distribution. Welch’s  $t$ -test is two-sided and measures whether two distributions have the same average. The distributions and averages significantly differ among functional and social communication networks across all features.

Feature	KS test		Welch’s $t$ -test	
	Test value	$p$ value	Test value	$p$ value
No. of users	0.25	$1.53e-05$	5.53	$7.194e-08$
No. of communications	0.43	$2.34e-16$	5.96	$1.22e-08$
Average clustering	0.31	$2.93e-08$	-7.31	$1.77e-12$
Job-title assortativity	0.95	$3.12e-95$	-39.59	$7.76e-136$
Degree assortativity	0.74	$1.55e-15$	-20.70	$1.38e-64$
Gini coefficient	0.25	$1.53e-05$	1.96	0.05
Density	0.39	$5.84e-13$	-9.13	$1.11e-17$

network feature. In particular, we apply (i) the Kolmogorov–Smirnov test to measure whether the feature distributions of functional and social networks are the same and (ii) Welch’s  $t$ -test to measure the difference between their averages. The results are presented in Table 1. Both the distributions and averages significantly differ among both types of networks across all features ( $p < 0.001$  in all cases, with the exception of the Gini coefficient for social networks, where  $p < 0.05$ ).

## 6. Dynamics of Network Metrics

We analyze the dynamics of functional and social communication networks by calculating the evolution of network features over time. We calculate these metrics cumulatively for each network at each month. The monthly data are then normalized into ten equally spaced bins between each company’s earliest and oldest work orders. In Figure 8, we present the average curve across all companies and error bars representing the standard error for each feature.

Figures 8(a) and 8(b) show the distributions of network size in terms of users and edges over time. For both types of networks, the number of users grows linearly, while the number of communications grows supralinearly. The different growth rates between population and interactions are consistent with scaling laws of human behavior [44]. Just like communication in cities and other social systems [45], the number of possible interacting individuals increases explosively due to a combinatoric effect of the existing population. As systems grow, the number of combinations increases much faster than the number of elements. Similar scaling laws have explained GDP growth and technological innovation [46]. In terms of management, it shows that the number of possible teams that can arise from a set of workers grows faster than the size of the company [16].

Through time, social communication networks seem to be more cohesive than functional networks, which is shown in a consistently higher network density (Figure 8(c)) and average clustering coefficient (Figure 8(d)). Although seemingly converging, the network density slightly decreases over time which can be due to the addition of new users to the

platform. On the other side, the average clustering seems to rapidly converge over time and remain stable.

The average Gini coefficient increases over time among both functional and social communication networks. This means that new connections disproportionately originate or are directed to those nodes that already account for a large number of connections. While such a principle is related to the rich-get-richer mechanism [7], the values we obtain are considerably higher than artificial Barabasi–Albert or real friends’ networks [47]. Moreover, consistently with the results presented in Section 5, the Gini coefficient of functional networks is always higher than that of social communications (Figure 8(e)), indicating that, at every point in time, most functional networks are more centralized.

Figure 8(f) shows the assortativity by degree coefficient of all enterprises over time. Across the whole observation period, functional communication networks have a negative assortativity by degree, while social ones have no correlation. This shows that functional communication networks are consistently more asymmetrical than social communication networks. On the contrary, Figure 8(g) shows that social networks (orange) are increasingly more segregated by job title than functional ones. While the segregation by job title in functional networks stays roughly uncorrelated, social networks become more and more segregated over time. This shows that functional networks are used for communication across layers of the organization, while social communication is used among team members of similar level.

In order to further analyze the group structure in functional and social communication networks, we calculate the average number of communications over time among the different job titles and across all companies. Results for social communications are shown in Figure 9 and for functional communications in Figure 10. In both figures, (a) to (d) show communications originated from supervisors, managers, operators, and executives, respectively. In each panel, orange, blue, light blue, and red lines show communications being received by supervisors, managers, operators, and executives, respectively. In social networks, the number of segregated communications by job title increases remarkably faster than the number of crossed interactions (Figure 9). In the case of supervisors (Figure 9(a)), such an increase seems to be linear, while in the case of managers (Figure 9(b)) and operators (Figure 9(c)), the number of segregated communications seems to accelerate in time. On the contrary, the segregation of formal communications is not analogous. In this case, top-down communications seem to be more (or just as) relevant as the segregated interactions.

## 7. Characterizing Enterprise Efficacy

In order to determine how functional and social communication network patterns influence enterprise efficacy, we define a score per enterprise based on the timely completion of their work orders. We define a work order’s score according to the following equation:

$$s_i = \frac{d_i - c_i}{d_i - a_i}, \quad (1)$$

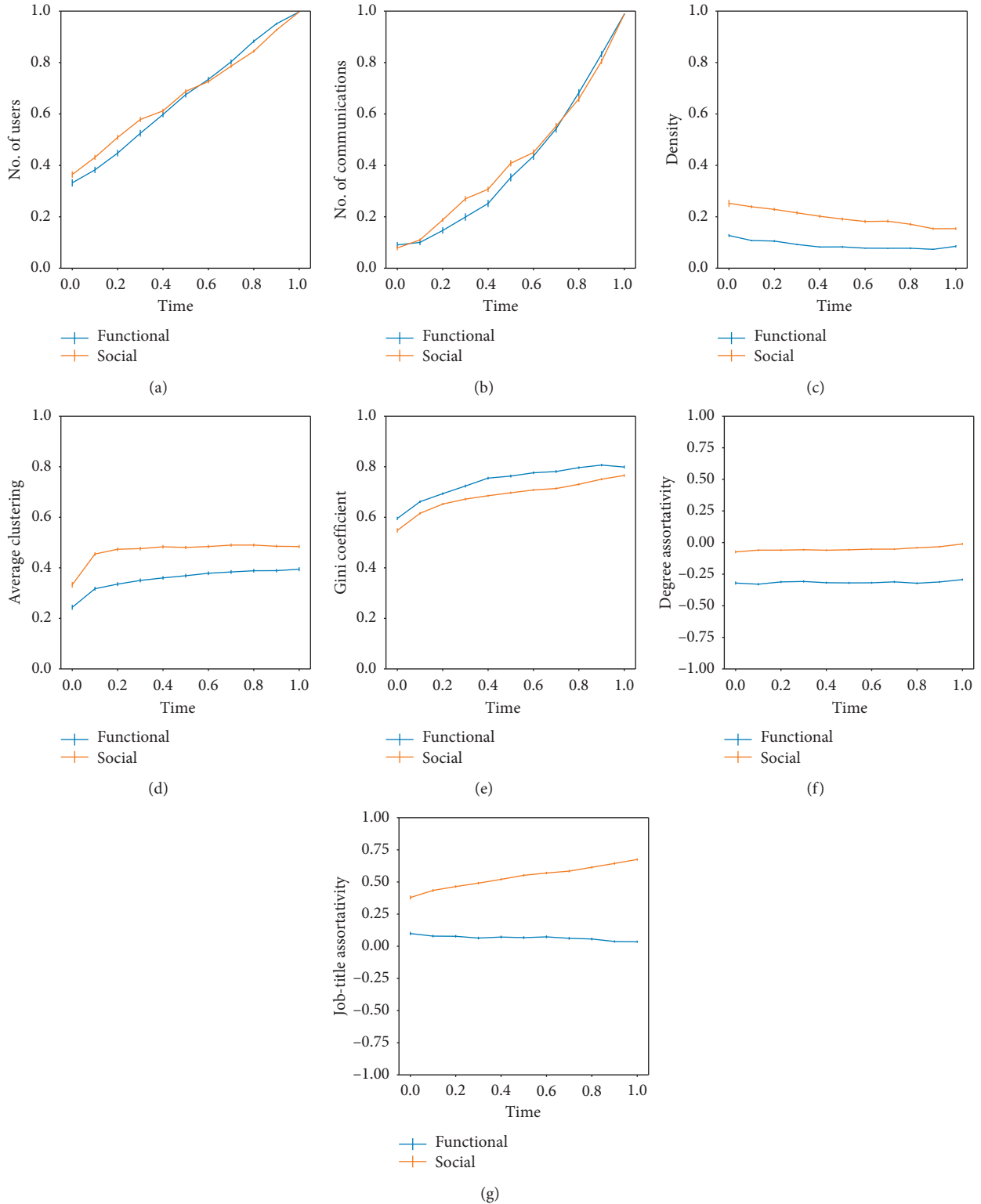


FIGURE 8: Dynamics of properties of functional (blue) and social (orange) networks for all enterprises. (a) No. of users per functional and social networks over time. (b) No. of communications per functional and social networks over time. (c) Density per functional and social networks over time. (d) Average clustering per functional and social networks over time. (e) Gini coefficients for functional and social networks' degree distributions over time. (f) Degree assortativity for functional and social networks over time. (g) Job-title assortativity for functional and social networks over time. Error bars indicate the standard error.

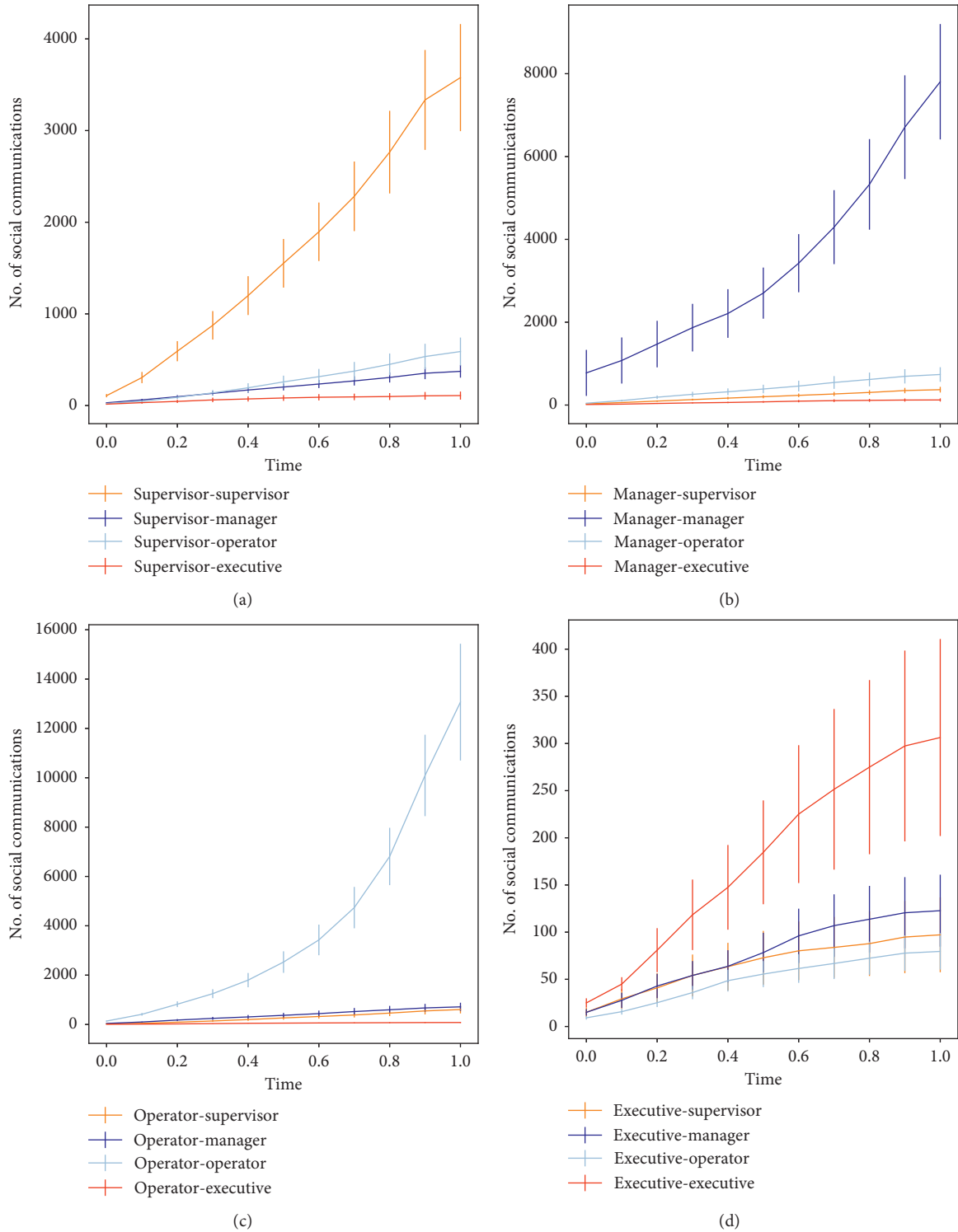


FIGURE 9: Average number of level-to-level communications of social networks over time for all enterprises. (a–d) Communications originated by supervisors, managers, operators, and executives, respectively. Orange, blue, light blue, and red lines show communications directed to supervisors, managers, operators, and executives, respectively. Error bars indicate the standard deviation. An analogous plot for formal communications is shown in Figure 9.

where  $a_i$  is the time when the work order  $i$  was assigned,  $d_i$  is the time it was due,  $c_i$  is the time it was completed, and  $s_i$  is the resulting score. A negative score indicates

the work order was completed earlier than scheduled, a positive score indicates the work order was completed late, and a score of zero indicates the work order was

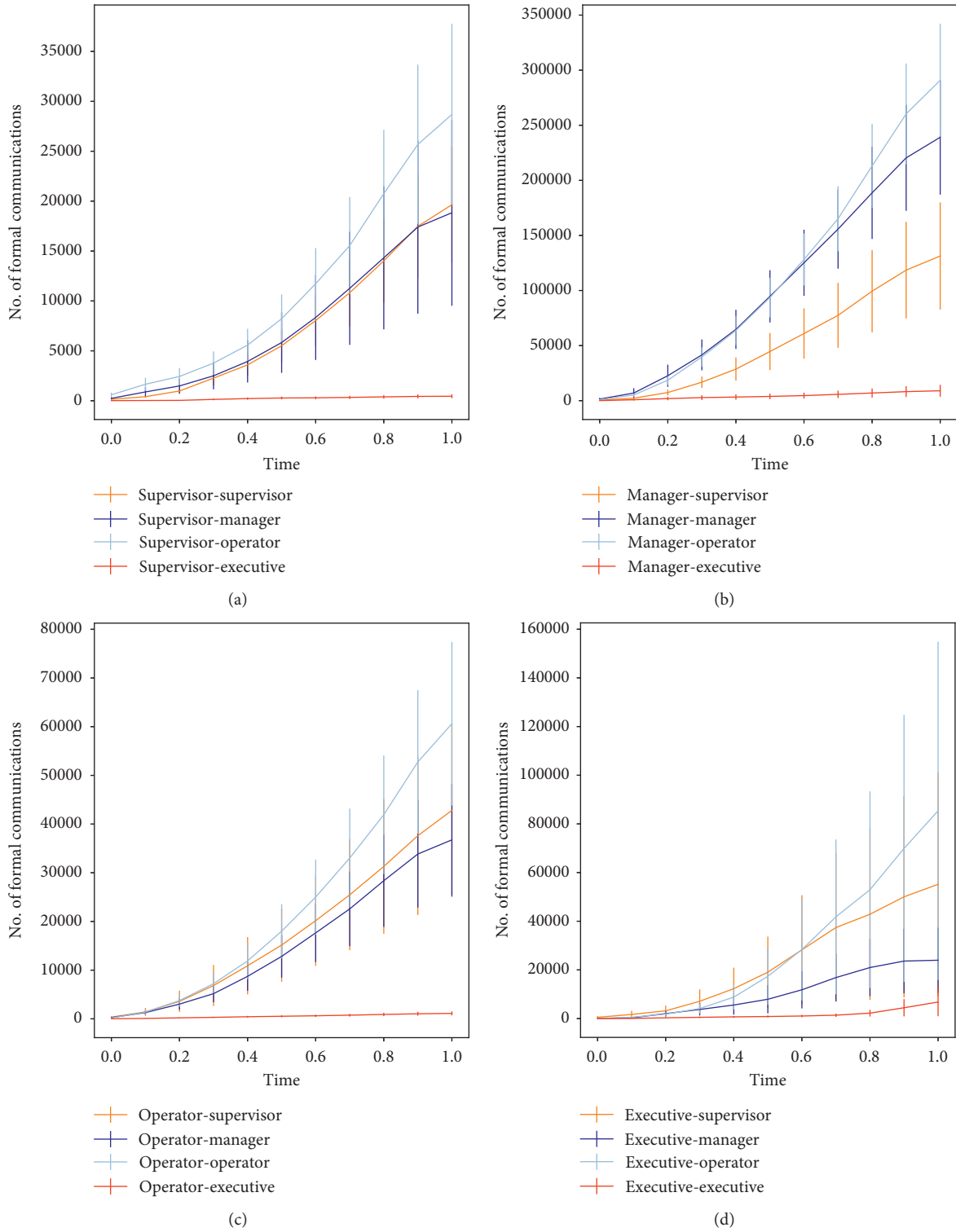
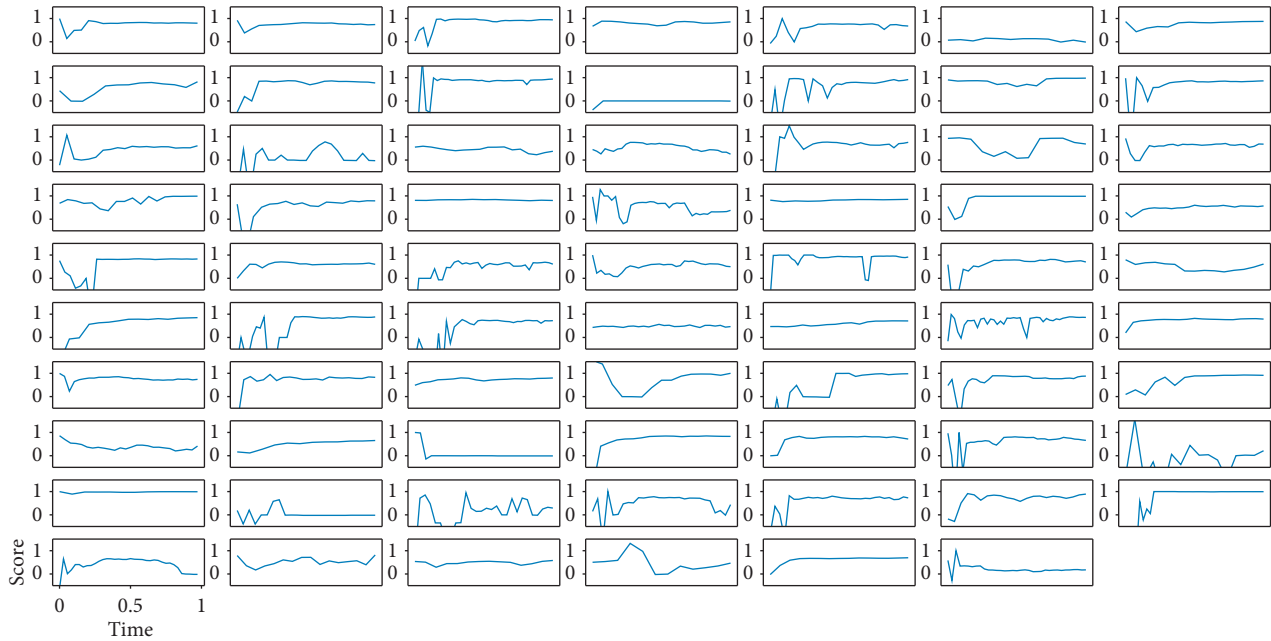


FIGURE 10: Average number of level-to-level communications of functional networks over time for all enterprises. (a–d) Communications originated by supervisors, managers, operators, and executives, respectively. Orange, blue, light blue, and red lines show communications directed to supervisors, managers, operators, and executives, respectively. Error bars indicate the standard deviation. An analogous plot for social communications is shown in Figure 9.

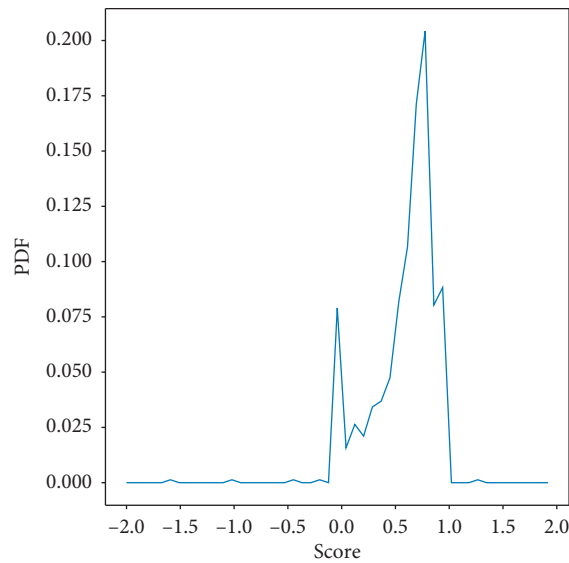
completed on time. In general, lower scores indicate better efficacy.

We analyze efficacy on monthly basis. We aggregate enterprises’ work orders per month and calculate their

median score. Efficacy varies across enterprises. Figure 11(a) shows the time series of the efficacy score for companies that have been active for at least one year. In general, companies go through a transition period before



(a)



(b)

FIGURE 11: Efficacy score for selected enterprises. (a) Efficacy score time series of enterprises with at least one year of activity. (b) Distribution of the monthly efficacy score over the last year of activity.

stabilizing their score. Figure 11(b) shows the distribution of enterprises' monthly scores over the last year of activity where the behavior is mainly stable. The distribution is bimodal, with a peak just below zero and another, more prominent peak between zero and one. Since a score of  $s_i = 0$  indicates that the work order is done on time, the smaller peak below zero is enterprises that are completing the majority of their work orders early. The larger peak between zero and one indicates that most enterprises are completing a majority of their work orders late. A score of  $s_i = 1$  indicates that the work order took 100% or more of the time allotted. The tail trailing

behind the first peak comprises a small set of effective enterprises.

We correlated monthly network features with the corresponding scores for each enterprise in order to determine the influence of each property on efficacy. We consider only the last twelve months of activity. Analogously with scores, network features are also calculated on the monthly basis without aggregating edges across months. We characterize each corporation with the following network properties for both functional and social interactions: the number of nodes (users), number of edges (communications), average clustering, assortativity by degree and job title, inequality in

TABLE 2: Correlation coefficients of functional and social communication network features with the efficacy score. Positive coefficients indicate that the feature correlates with a worse score. Negative coefficients indicate that the feature correlates with a better score. The number of users and that of communications are in the logarithmic scale. Correlations coefficients are significant ( $p < 0.001$ ). Not significant coefficients are not shown.

	Network	
	Functional	Social
No. of users	0.27	0.20
No. of communications	0.27	—
Average clustering	—	-0.17
Degree assortativity	—	0.17
Job-title assortativity	0.26	—
Gini coefficient	0.17	—
Density	-0.11	-0.23

connections (measured via the Gini coefficient of the degree distribution), and density. In Table 2, we present the correlation of these features with the scores. A negative correlation indicates an improvement of efficacy, and a positive correlation shows a deterioration. Missing correlations are not statistically significant.

The number of users in both functional and social communication networks is correlated with inefficacy (positive correlation coefficient with the score), which may mean that larger corporations perform worse than smaller ones. Analogously, the number of functional communications is associated with a worse efficacy, which can be related to the size of the company, but may also indicate that adverse times require more communication for completing tasks. Inequality in functional interactions and the degree assortativity of social networks correlate positively with the score, meaning that more asymmetrical networks are associated with inefficacy. Efficacy is instead associated with the density of the networks. Density correlates negatively with the score, meaning that effective teams are characterized for having a larger number of interacting individuals. This is also reflected in the average clustering of social networks. The correlation of other metrics with the score does not seem to be statistically significant. An analogous analysis applied to the average behavior over time rather than the monthly breakdown is shown in Supplementary Materials (Section S3). The results are consistent.

Finally, we study the aggregate structure of the data by applying principal component analysis (PCA) to enterprises based on functional and social communication monthly network features including the corresponding score. The PCA is calculated by constructing a matrix where rows are monthly observations of enterprises and columns represent the corresponding network features and score. This analysis enables the decomposition of the manifold in a reduced set of new dimensions that show dominant behaviors. Components are ordered by the amount of variance they explain. In this case, the two main components explain up to 77% of the variance. In Table 3, we show the coefficients of network features and score in

TABLE 3: Principal component analysis (PCA) of functional and social communication networks and efficacy score. Coefficients of each feature for the first (PC-1) and second (PC-2) components are shown. Together, the main two components explain up to 76% of the variance (explained variance by component in parentheses).

	PC-1 (55%)		PC-2 (21%)	
	Functional	Social	Functional	Social
No. of users	-0.26	-0.19	-0.05	-0.18
No. of communications	-0.91	-0.23	0.28	-0.91
Average clustering	-0.02	0.01	-0.04	-0.12
Degree assortativity	0.01	-0.01	0.03	0.02
Job-title assortativity	-0.01	-0.04	0.08	-0.16
Gini coefficient	-0.05	-0.03	0.01	-0.04
Density	0.02	0.05	-0.002	-0.03
Efficacy score	-0.10		0.08	

each component. The first component (PC-1) is dominated by the number of functional communications, and the second component (PC-2) is dominated by the number of social communications. In both cases, the components are in the inverse direction of the number of communications, meaning that features in the direction of the component are inversely proportional to the number of communications. Good scores are in the direction of the first component, and bad scores are in the direction of the second component. Similarly, network density and average clustering in social communications increase in the direction of the first component and decrease in the direction of the second. This shows that effective companies are characterized for having less functional communication and higher social communication—especially in terms of the density and clustering of connections.

In order to understand these composite relationships, we present scatter plots of the two main components in Figure 12. Each dot is a company at a given month, and the location in the scatter plot shows the dot product of the company’s feature vector and the corresponding component (PC-1 in the  $x$ -axis and PC-2 in the  $y$ -axis). Panels are colored by different features (see titles). We identify three regions in the space. Region A corresponds to big companies (red and green dots in panels (a) and (e)). Region B shows effective companies (blue dots in panel (i)). Region C shows ineffective companies (red dots in panel (i)). Big companies in region A are generally more ineffective than smaller companies in regions B and C. Effective companies in region B are characterized for having lower functional communication (blue in panel (b)) and varied number of social communications (from red to blue in panel (f)). They also have higher density in both types of networks (red in panels (c) and (g)) and higher clustering in social communication networks (red in panel (h)). Ineffective companies in region C are characterized for having a higher number of functional communications, lower number of social communications, and lower density and clustering coefficient in social networks. More features are presented in Supplementary Materials (see Section S4).

These results show that certain social behaviors may be associated with efficacy in industrial settings. In particular,

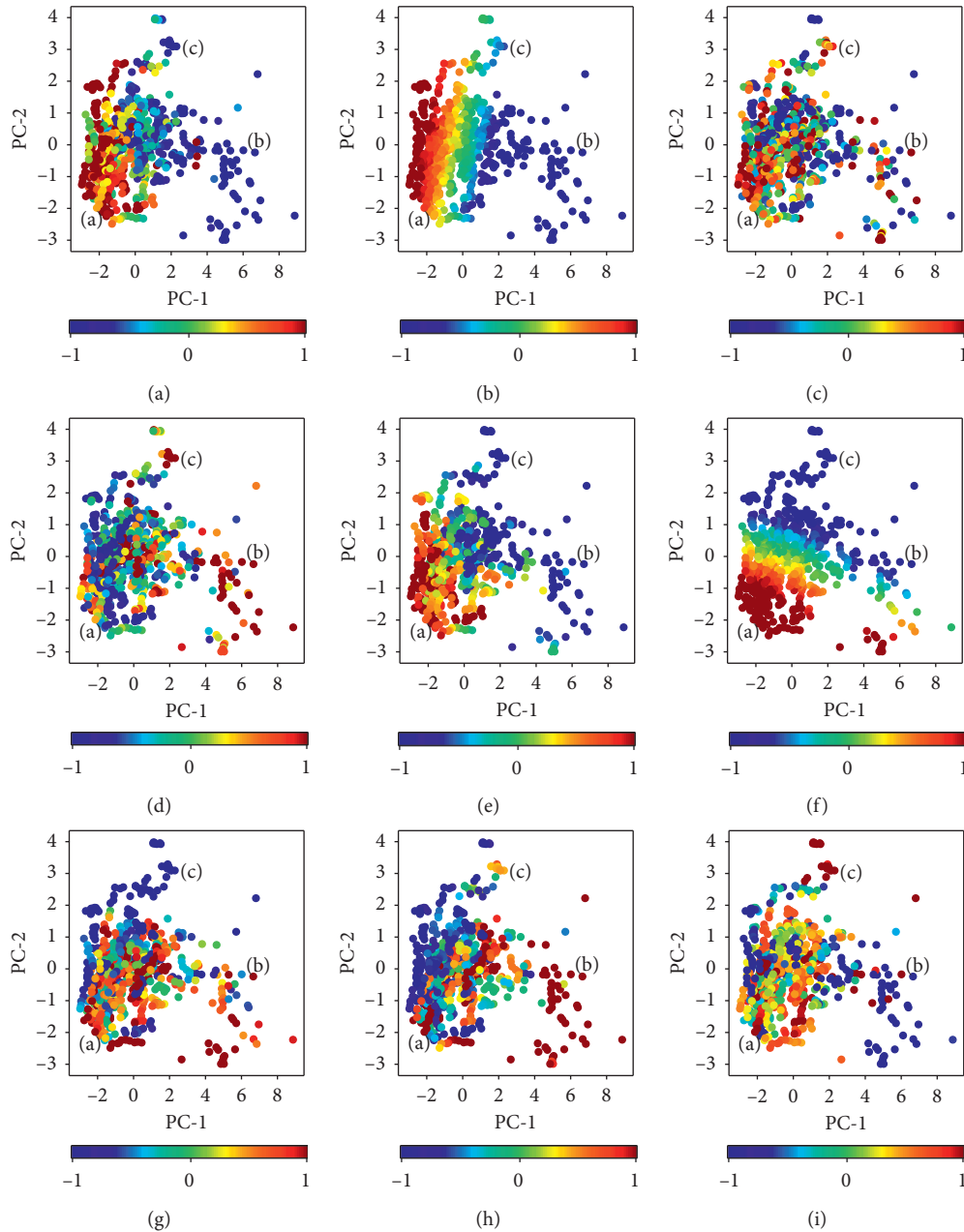


FIGURE 12: Principal component analysis (PCA) of enterprises based on functional and social communication monthly network features including the corresponding efficacy score. Dots represent individual companies at particular months. Their location in the scatter plots shows the dot product of the company's feature vector and the corresponding component (PC-1 in the  $x$ -axis and PC-2 in the  $y$ -axis). Panels are colored by different features (see titles). Features have been normalized by subtracting the average and dividing by the standard deviation (scale on figure). The number of functional and social communications is in the logarithmic scale. Regions (A), (B), and (C) indicate the location of big, effective, and ineffective companies, respectively. More features are presented in Supplementary Materials (see Section S4). (a) Functional users. (b) Functional communications. (c) Functional clustering. (d) Functional density. (e) Social users. (f) Social communications. (g) Social clustering. (h) Social density. (i) Score.

excessive functional communication can be detrimental for timely completion of tasks and digital social interactions may be beneficial. However, being effective on finishing work orders is not necessarily equivalent to improving labour productivity in terms of volume produced in labour hours, which is out of the scope of this study. A further investigation of the relationship between human dynamics

and other labour productivity measures is still necessary for advancing such understanding.

## 8. Conclusion

We constructed and characterized digitized functional and social communication networks from industrial production



plants and determined the network patterns that distinguish both types of interactions and affect team efficacy, in terms of the timely completion of work orders. We found that functional communication networks are asymmetrical and social-media-style communication networks are segregated by job title. We showed that efficacy is negatively associated with the number of functional communications but positively associated with the density of social communication networks. This shows that, beyond the volume of communications, the complexity of interactions matters for improving performance.

Effective industrial-management software is critical to enterprise performance. Among the enterprises we analyzed, those with more functional communications performed worse than others, which had a combination of less functional communication together with an increased density of social communications. While functional and structured communications support the organization, it is important to identify that newer and easier means to communicate with workers, and workers to communicate with one another, increase efficacy and improve overall performance.

### Data Availability

The network data used to support the findings of this study are available from the corresponding author upon request.

### Conflicts of Interest

The authors declare that they have no conflicts of interest.

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### Supplementary Materials

Figure S1: complementary cumulative distribution function (CCDF) of companies' life-span measured in months. Table S1: correlation coefficients of functional and social communication average network features with the average efficacy score. Figure S2: visualization of functional communication networks from all enterprises. Figure S3: adjacency matrices of functional communication networks from all enterprises. Figure S4: visualization of social communication networks from all enterprises. Figure S5: adjacency matrices of social communication networks from all enterprises. Figure S6: distribution of the efficacy scores for all enterprises. Lower scores indicate better efficacy. Figure S7: principal component analysis (PCA) of enterprises based on functional and social communication monthly network features including the corresponding efficacy score. (*Supplementary Materials*)

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