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THE STRUCTURE OF COMMUNICATION NETWORKS IN HUMAN-ALGORITHMIC INTERACTION

This study examines communication networks in three IT organizations. It focuses on how human-algorithmic interaction fits into existing patterns of organizational communication. Social network analysis (SNA) was used to compare three forms of interaction: within functional groups, between functional groups, and between these groups and AI. AI was represented as a separate digital node in each organizational network. The results show that communication is denser within functional groups than between them. Intergroup ties are less dense and are concentrated between particular groups. In contrast, functional groups interact with AI more extensively than with one another. Group-to-AI density exceeds intergroup density in all three organizations. This pattern shows that intensive interaction with AI can coexist with limited cross-functional communication. Thus, the widespread use of AI across functional areas does not necessarily correspond to stronger structural ties between them.

Keywords: *business administration, management, digital transformation, artificial intelligence, human-algorithmic interaction, social networks, communication, people management.*

JEL Classification: *M0, M1.*

СТРУКТУРНІ ОСОБЛИВОСТІ КОМУНІКАЦІЙНИХ МЕРЕЖ В УМОВАХ ЛЮДИНО-АЛГОРИТМІЧНОЇ ВЗАЄМОДІЇ

У статті досліджено структуру комунікаційних мереж трьох продуктових ІТ-організацій та місце людино-алгоритмічної взаємодії в наявній системі організаційних комунікацій. Метою дослідження є визначення структурних відмінностей між внутрішньогруповою, міжгруповою та людино-алгоритмічною взаємодією, а також особливостей їх поєднання в межах однієї організаційної мережі. Методологічною основою дослідження є аналіз соціальних мереж (SNA). Емпіричні дані зібрано за допомогою онлайн-опитування, під час якого працівники визначали, до кого вони звертаються за професійною підтримкою, включаючи колег і штучний інтелект. На основі отриманих відповідей для кожної організації сформовано направлені комунікаційні мережі. Штучний інтелект представлено як окремий цифровий вузол, що дало змогу аналізувати взаємодію працівників із ШІ в межах загальної структури мережі. Щільність мережі розраховано для трьох рівнів: усередині функціональних груп, між функціональними групами та між окремими групами і ШІ.

Результати засвідчили, що в усіх трьох організаціях середня внутрішньогрупова щільність перевищує середню міжгрупову, хоча інтенсивність внутрішніх комунікацій помітно відрізняється між функціональними групами. Міжгрупові зв'язки є менш щільними та мають вибірковий характер: сильніші комунікації зосереджені між окремими групами, а не рівномірно розподілені в організації. Інший характер має взаємодія зі штучним інтелектом. У всіх досліджуваних організаціях середня щільність взаємодії функціональних груп із ШІ суттєво перевищує середню щільність міжгрупових зв'язків.

Отримані результати показують, що інтенсивна взаємодія зі ШІ може поєднуватися з обмеженою міжфункціональною комунікацією. Використання ШІ в різних функціональних сферах саме по собі не означає посилення структурних зв'язків між ними. Для управління це підкреслює необхідність розглядати інтеграцію ШІ разом із наявною структурою внутрішньогрупових і міжфункціональних комунікацій. Такий підхід дає змогу розглядати людино-алгоритмічну взаємодію не ізольовано, а як складову організаційної комунікаційної мережі та точніше оцінювати її місце у взаємодії функціональних груп.

Ключові слова: *бізнес-адміністрування, менеджмент, цифрова трансформація, штучний інтелект, людино-алгоритмічна взаємодія, соціальні мережі, комунікація, управління персоналом.*

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Statement of the problem. Artificial intelligence is becoming increasingly integrated into everyday organizational processes and changing the environment in which employees perform their work. AI tools are used to support information processing, decision-making, task performance, and other professional activities. As their role expands, interaction with artificial intelligence becomes part of organizational processes that previously relied primarily on communication and knowledge exchange between employees. This development makes it necessary to consider AI integration not only as a technological change but also in relation to the transformation of organizational interaction.

The importance of this problem is supported by recent studies of human–AI collaboration. Faraj et al. (2018) show that the integration of learning algorithms transforms organizational practices, professional expertise, boundaries, and coordination. Orlikowski and Scott (2008) similarly argue that technology, work, and organization are closely interconnected and should not be considered separately. More recent research demonstrates that these changes also concern interaction between organizational participants. Meng et al. (2025) found that employee–AI collaboration can influence interpersonal communication and social interaction in the workplace. At the same time, Dell'Acqua et al. (2025) demonstrate that AI can participate directly in collaborative work and perform functions that were previously associated mainly with human participants.

These changes are particularly important from the perspective of organizational communication networks. Communication ties support the exchange of information and knowledge and connect employees who belong to different parts of an organization. The structure of these relationships therefore affects how organizational participants interact and how information moves across organizational boundaries. Classical network research also demonstrates the importance of connections between different social groups. Granovetter (1973) showed the role of weak ties in providing access to information beyond an individual's immediate social environment, while Burt (2004) demonstrated the importance of connections between otherwise disconnected groups for access to diverse information and ideas.

The growing involvement of AI introduces an additional component into this system of relationships. Employees can obtain information and support not only from colleagues but also from algorithmic systems. Previous research indicates that human–AI collaboration may change interpersonal interaction, while AI can become directly involved in collaborative activities. However, the existence of a common technological resource does not by itself describe how communication is structured within an organization. Analysis of organizational interaction therefore requires attention both to communication among employees and to their interaction with AI.

This problem becomes especially relevant when communication is considered at the level of functional groups. Relationships within a functional group and relationships connecting different groups represent different dimensions of organizational communication. At the same time, employees from these groups may interact with the same AI tools as part of their work activities. Examining these dimensions together makes it possible to investigate how intragroup communication, intergroup communication, and interaction with AI are structured within the same organizational network. Such an analysis is necessary for a more detailed understanding of the structural characteristics of communication networks in the context of human-algorithmic interaction.

Analysis of recent research and publications. Digital transformation has expanded from the introduction of individual technologies to broader changes in organizational activities and management processes. Sacavém et al. (2025) emphasize that technological development is accompanied by structural, operational, and cultural changes within organizations. This understanding shifts attention from technology itself to the organizational environment in which it is introduced. In this context, Afriliana and Ramadhan (2022) provide a more detailed view of the areas affected by digital transformation. Their research shows that these changes extend to organizational functions, processes, operations, services, and products. Thus, digital transformation gradually changes not only how particular tasks are performed but also how organizational activities are structured and coordinated.

Changes in coordination become especially important when digital transformation affects the organizational structure itself. Robinson (n.d.) associates this process with greater flexibility, decentralization of decision-making, and increased employee autonomy. These structural changes are supported by digital platforms that facilitate collaboration and access to information. As a result, coordination becomes less dependent on traditional hierarchical channels and increasingly involves direct interaction between different parts of the organization. This shift brings communication to the centre of structural transformation because new organizational arrangements require corresponding patterns of information exchange and collaboration.

The relationship between structural transformation and communication is further developed by Deep (2023) through the analysis of organizational culture. The author connects digital transformation with a movement from rigid hierarchical structures towards more flexible and decentralized forms of organization. Such changes are accompanied by the development of virtual communication channels that support collaboration and knowledge exchange. They also create conditions for stronger interaction across functional boundaries, where employees from different areas need to coordinate their activities. Communication can therefore be viewed as one of the mechanisms through which broader structural changes become embedded in everyday organizational practices.

The content of these practices is also changing as digital technologies become more deeply integrated into operational and managerial processes. Sheremeta (2024) links intelligent technologies with the automation of routine tasks and the optimization of workflows, showing how technology becomes involved in everyday organizational

activities. This development increases the role of information and data in management, which creates a basis for more data-driven approaches to decision-making. Yang (2025) examines this shift through the growing use of data and analytical methods in managerial processes. The development of AI-enhanced analytics extends this tendency further, as Lindeman (2025) associates such technologies with faster decision-making, forecasting, and resource allocation. Together, these changes demonstrate a gradual expansion of the technological component within activities that previously relied primarily on human participation.

The increasing use of artificial intelligence adds a new dimension to this transformation because employees begin to interact directly with technological systems during their work. AI can become involved in information processing, task performance, and decision support, making human-algorithmic interaction part of everyday organizational activities. At the same time, these interactions do not develop separately from existing relationships between employees and functional units. They become embedded in an organizational environment that already has established patterns of communication and coordination. This creates a need to examine human-algorithmic interaction in relation to the communication structure in which it occurs.

Formal organizational structures provide only limited possibilities for such analysis because they describe assigned positions rather than actual patterns of interaction. Employees within the same functional group may communicate with different intensity, while relationships between functional groups may follow another pattern. The use of AI introduces an additional type of interaction whose intensity may also vary across organizational units. Consequently, understanding the emerging communication structure requires an approach that can capture actual relationships within groups, across their boundaries, and between human actors and AI.

Social network analysis provides the methodological basis for examining organizational structures from this relational perspective. Wasserman and Faust (1994) conceptualize social structures through actors and the ties connecting them, which allows attention to shift from formal organizational positions to actual relationships. Hanneman and Riddle (2005) develop this perspective by explaining how different network characteristics can reveal patterns in the distribution of these relationships. This analytical logic is also reflected in the work of Rawlings et al. (2023), who integrate social network theory with methods for studying relational structures. Taken together, these approaches provide a basis for examining organizational communication as a network whose structure emerges from the configuration and intensity of interactions between its actors.

Within such a network, density is particularly relevant because it characterizes the intensity of connections in relation to the number of possible relationships. Its application to different parts of the same organizational network allows communication within functional groups to be compared with communication across their boundaries. This distinction is important because a network may contain internally cohesive groups without equally intensive relationships between them. When AI is represented as a separate digital node, its relationships with functional groups can be examined within the same analytical framework. This makes it possible to distinguish between intragroup, intergroup, and human-algorithmic interaction without treating them as equivalent forms of communication.

Despite these developments, an important aspect of organizational communication remains insufficiently examined. Existing studies do not provide a clear understanding of how communication within functional groups and between them is structured in relation to employees' interaction with AI. In particular, it remains unclear whether differences in the intensity of intragroup and intergroup communication are also reflected in the interaction of functional groups with AI as a separate digital node. This limits the understanding of how human-algorithmic interaction is embedded in the existing communication structure of an organization. The unresolved problem, therefore, lies in identifying and comparing the structural characteristics of intragroup, intergroup, and human-algorithmic interactions within the same organizational communication network.

Purpose of the article. This article examines the structure of communication networks in product IT organizations where employees interact with AI. The analysis focuses on communication within functional groups, between different groups, and with AI as a separate digital node. By examining these three dimensions within the same organizational network, the study aims to identify and compare their structural characteristics and determine how they are related within the overall communication structure.

Research methods. The following methods were applied to achieve the research objectives: methods of analysis and synthesis - for systematizing theoretical approaches to communication networks and human-algorithmic interaction; method of online survey - for collecting data on interactions between employees and between employees and AI; comparative method - for identifying structural differences among the three organizations; statistical methods, including Z-transformation and calculation of mean values, - for standardizing and comparing network density indicators.

Main results of the study. The analysis of the communication networks began with an assessment of their overall density to determine the general level of connectivity in each organization. The results show that all three networks are characterized by low density. Company A has the highest value of 0.107, which means that approximately 11% of all possible directed ties are realized within the network. Company C has a density of 0.082, corresponding to approximately 8% of possible ties, while Company B has the lowest value of 0.077, or 7.7%. Thus, despite differences between the three organizations, direct communication ties represent only a limited proportion of all possible connections within each network.

The average degree provides additional information about direct connectivity within these networks. The highest value is observed in Company A (4.512), followed by Company C (4.418) and Company B (3.780). This means that participants maintain, on average, approximately four

direct connections within each of the three organizational networks. Together with the density values, these results provide a general description of the communication networks before their internal structure is examined in greater detail (Table 1).

The analysis was then conducted at the level of functional groups to examine how communication is distributed within the organizational structure. This makes it possible to distinguish differences in internal connectivity between functional units and to identify how strongly communication ties are concentrated within individual groups.

Table 1

General characteristics of the communication networks

Indicator	Company A	Company B	Company C
Overall network density	0.107	0.077	0.082
Number of ties	194	189	243
Average degree	4.512	3.780	4.418

Source: calculated by the author using UCINET for Windows.

A more detailed analysis of Company A shows that communication within functional groups varies considerably across the organization. Support (0.600), HR (0.583), and QA (0.583) have relatively dense internal networks. Employees in these groups are connected through a broader range of direct communication ties, providing more channels for information exchange and coordination within the team. Finance (0.450) shows a moderate level of internal connectivity, suggesting that communication is less widely distributed across the group.

A different pattern is observed in Marketing (0.381), Sales (0.339), and Development (0.262), where internal networks are less dense. Communication in these groups involves a smaller share of the possible connections between employees and is therefore more selective. This may make internal information exchange more dependent on particular communication ties and reduce the number of alternative channels available for coordination. Overall, the results show that employees in Company A do not operate under the same communication conditions across functional units. For management, this difference is relevant because the way information circulates and coordination takes place within teams depends partly on how broadly communication ties are distributed among their members.

C-Level and the AI node were excluded from the intragroup analysis presented in Table 2. Empirical data for C-Level were unavailable, while AI represents a separate digital node and therefore does not have an internal communication structure.

Table 2

Intragroup density of functional groups in Company A

Group	Density	Mean density	Squared deviation	Variance	Standard deviation	Z-score
Finance	0.450	0.457	0	0.016	0.125	−0.05
HR	0.583		0.016			1.01
Marketing	0.381		0.006			−0.61
Sales	0.339		0.014			−0.94
Development	0.262		0.038			−1.55
QA	0.583		0.016			1.01
Support	0.600		0.02			1.14

Source: calculated by the author using UCINET for Windows and Excel

Company B shows a more fragmented pattern of communication within its functional groups. C-Level, Finance, Sales, and AI integrations (0.500) have relatively dense internal networks, indicating that communication in these groups is distributed across a substantial share of the possible connections between their members. Customer Support (0.333) and Marketing (0.250) are less internally connected, while Development (0.167), Customer Success (0.150), and Analytics (0.125) have considerably sparser communication networks. In these groups, internal information exchange relies on a relatively limited set of direct relationships.

The strongest contrast is observed in HR, Coding, and Offline, where no intragroup ties were recorded. This does not necessarily indicate an absence of work-related interaction, but it shows that the analyzed network does not contain direct communication ties among members of these groups. Overall, Company B combines functional units with relatively broad internal communication networks and units where communication is much more limited or absent within the group. From a management perspective, these differences indicate that the number of direct channels available for internal information exchange and coordination varies considerably across functional units. Groups with sparse internal networks may depend more strongly on particular communication ties or on relationships outside their own functional unit (Table 3).

Table 3

Intragroup density of functional groups in Company B

Group	Density	Mean density	Squared deviation	Variance	Standard deviation	Z-score
C-Level	0.500	0.252	0.061	0.040	0.199	1.24
Finance	0.500		0.061			1.24
HR	0.000		0.064			-1.26
Marketing	0.250		0.000			-0.01
Sales	0.500		0.061			1.24
Development	0.167		0.007			-0.43
Customer Success	0.150		0.010			-0.51
Customer Support	0.333		0.007			0.41
Analytics	0.125		0.016			-0.64
Coding	0.000		0.064			-1.26
Offline	0.000		0.064			-1.26
AI integrations	0.500		0.061			1.24

Source: calculated by the author using UCINET for Windows and Excel.

Company C shows a strong contrast in the way communication is organized within its functional groups. Administration, Sysadmin, and R&D (1.000) have fully connected internal networks, meaning that all possible communication ties within these groups are present in the analyzed network. Marketing (0.900) also has a highly connected internal structure, while Finance (0.667) maintains relatively broad communication among its members. These groups therefore have a larger number of direct channels available for internal information exchange and coordination.

Communication is considerably more selective in QA (0.300), Development (0.244), Sales (0.222), HR (0.167), and Customer Support (0.139). In these groups, employees are connected through a much smaller share of the possible internal ties. Information exchange and coordination may therefore depend more strongly on particular communication relationships rather than being broadly distributed across the group. The coexistence of highly connected and relatively sparse internal networks indicates that communication conditions differ substantially across the functional structure of Company C. From a management perspective, these differences are important because functional units have different numbers of direct communication channels available for internal information exchange and coordination (Table 4).

Table 4

Intragroup density of functional groups in Company C

Group	Density	Mean density	Squared deviation	Variance	Standard deviation	Z-score
C-Level	0	0.513	0.263	0.146	0.383	−1.34
Admin.	1		0.238			1.27
Finance	0.667		0.024			0.4
HR	0.167		0.119			−0.90
Sysadmin	1		0.238			1.27
Marketing	0.9		0.15			1.01
Sales	0.222		0.084			−0.76
Customer Support	0.139		0.14			−0.98
Development	0.244		0.072			−0.70
QA	0.3		0.045			−0.56
R&D	1		0.238			1.27

Source: calculated by the author using UCINET for Windows and Excel.

The next stage of the analysis examines communication between functional groups together with their interaction with AI as a separate digital node. In Company A, communication across functional boundaries is relatively limited and concentrated in a small number of directed relationships. Among the strongest intergroup connections are those from Finance to C-Level (0.700), from Finance to HR (0.300), and from QA to Development (0.250). This pattern indicates that cross-functional communication is selective rather than broadly distributed across the organization, suggesting that information exchange between functional areas relies more strongly on particular communication channels, while many other potential connections between groups remain weak or absent.

Interaction with AI follows a different pattern. All functional groups for which empirical data are available demonstrate high levels of interaction with the AI node, ranging from Marketing (0.714) to HR, Sales, and Support (1.000). Interaction with AI is therefore widespread across functional areas even though direct communication between these areas remains comparatively limited. From a management perspective, this distinction is important because interaction with the same digital resource does not imply stronger communication across functional boundaries. In Company A, high levels of interaction with AI coexist with a cross-functional communication network that remains selective and concentrated in particular relationships (Table 5).

Table 5

Density of intergroup and human-algorithmic interactions in Company A

Department	C-Level	Finance	HR	Marketing	Sales	Development	QA	Support	AI node
C-Level	**0.000**	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Finance	0.700	**0.450**	0.300	0.000	0.075	0.114	0.000	0.040	0.800
HR	0.125	0.000	**0.583**	0.107	0.000	0.036	0.000	0.000	1.000
Marketing	0.143	0.000	0.000	**0.381**	0.036	0.041	0.000	0.000	0.714
Sales	0.125	0.025	0.094	0.054	**0.339**	0.107	0.000	0.150	1.000
Development	0.000	0.000	0.107	0.020	0.000	**0.262**	0.107	0.029	0.857
QA	0.000	0.000	0.125	0.000	0.000	0.250	**0.583**	0.000	0.750
Support	0.000	0.000	0.050	0.086	0.075	0.000	0.050	**0.600**	1.000
AI node	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	**0.000**

Source: calculated by the author using UCINET for Windows.

Company B also shows a selective pattern of communication across functional boundaries, although several strong intergroup connections are present. HR and Offline have particularly intensive communication with C-Level (1.000), while Finance also maintains a strong connection in this direction (0.750). HR is another important destination for communication from several functional areas, including Customer Success (0.800), Customer Support (0.667), Marketing (0.600), and Analytics and Coding (0.500). These relationships show that cross-functional communication is concentrated around particular organizational areas rather than broadly distributed between functional groups. Many other combinations have weak or no recorded ties, suggesting that interaction across functional boundaries relies more strongly on a limited number of communication channels.

Interaction with AI is much more widely distributed across the functional structure. HR, Marketing, Sales, Customer Success, Customer Support, Analytics, and Coding all demonstrate complete group-to-AI density (1.000), while Development also shows intensive interaction with the AI node (0.769). Lower levels are observed for C-Level and AI integrations (0.500), whereas Finance and Offline have no recorded interaction with AI. Thus, interaction with AI is widespread across most functional areas, although it is not observed equally across the entire organization. From a management perspective, this contrast is important because widespread human-algorithmic interaction coexists with a cross-functional communication structure that remains concentrated around selected relationships. AI represents a shared digital resource for many functional groups, but interaction with the same AI node does not correspond to equally broad communication between the functional areas themselves (Table 6).

Company C demonstrates an even stronger contrast between communication within particular functional groups and communication across their boundaries. Most intergroup relationships are weak or absent, while stronger connections are concentrated in only a few directions. The strongest cross-functional communication is directed towards C-Level, particularly from Administration (1.000) and R&D (0.750). Outside these relationships, cross-functional communication is considerably more limited. This pattern is particularly notable because several functional groups in Company C have highly connected internal networks. High internal connectivity within these groups therefore coexists with much more selective communication across functional boundaries.

Table 6

Density of intergroup and human-algorithmic interactions in Company B

Department	C-Level	Finance	HR	Marketing	Sales	Development	Customer Success	Customer Support	Analytics	Coding	Offline	AI integrations	AI node
C-Level	**0.500**	0.125	0.500	0.100	0.167	0.038	0.000	0.000	0.000	0.000	0.000	0.000	0.500
Finance	0.750	**0.500**	0.500	0.000	0.000	0.000	0.050	0.000	0.000	0.000	0.000	0.000	0.000
HR	1.000	0.250	**0.000**	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000
Marketing	0.400	0.050	0.600	**0.250**	0.000	0.015	0.040	0.133	0.000	0.000	0.000	0.000	1.000
Sales	0.500	0.000	0.333	0.133	**0.500**	0.000	0.000	0.111	0.000	0.000	0.000	0.000	1.000
Development	0.115	0.000	0.385	0.000	0.000	**0.167**	0.000	0.000	0.000	0.000	0.000	0.000	0.769
Customer Success	0.500	0.050	0.800	0.040	0.067	0.046	**0.150**	0.000	0.000	0.000	0.000	0.000	1.000
Customer Support	0.167	0.000	0.667	0.067	0.111	0.077	0.067	**0.333**	0.000	0.000	0.000	0.167	1.000
Analytics	0.125	0.031	0.500	0.025	0.083	0.029	0.000	0.042	**0.125**	0.000	0.000	0.375	1.000
Coding	0.000	0.000	0.500	0.000	0.000	0.000	0.000	0.000	0.125	**0.000**	0.000	0.250	1.000
Offline	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.333	0.000	0.000	**0.000**	0.000	0.000
AI integrations	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	**0.500**	0.500
AI node	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	**0.000**

Source: calculated by the author using UCINET for Windows.

Interaction with AI is distributed much more widely across the functional structure. Administration, Sysadmin, Marketing, and R&D show complete group-to-AI density (1.000), while high levels are also observed in Sales (0.889), QA (0.800), Customer Support (0.778), HR (0.750), and Development (0.700). C-Level (0.500) and Finance (0.333) interact with the AI node less intensively, but the overall pattern still shows that interaction with AI extends across all functional areas represented in the network. From a management perspective, Company C therefore combines strong internal connectivity in several functional groups with limited communication across many functional boundaries and widespread interaction with AI. Interaction with the same digital node across functional groups does not correspond to an equally interconnected cross-functional communication structure (Table 7).

Table 7

Density of intergroup and human-algorithmic interactions in Company C

Department	C-Level	Admin.	Finance	HR	Sysadmin	Marketing	Sales	Customer Support	Development	QA	R&D	AI node
C-Level	**0.000**	0.250	0.000	0.125	0.167	0.100	0.056	0.056	0.050	0.100	0.250	0.500
Admin.	1.000	**1.000**	0.167	0.250	0.000	0.100	0.056	0.000	0.000	0.000	0.000	1.000
Finance	0.167	0.333	**0.667**	0.167	0.000	0.067	0.000	0.000	0.000	0.000	0.000	0.333
HR	0.125	0.125	0.000	**0.167**	0.000	0.050	0.000	0.000	0.000	0.000	0.000	0.750
Sysadmin	0.000	0.000	0.000	0.083	**1.000**	0.000	0.000	0.000	0.067	0.000	0.000	1.000
Marketing	0.100	0.000	0.000	0.100	0.000	**0.900**	0.022	0.000	0.000	0.000	0.000	1.000
Sales	0.111	0.111	0.000	0.139	0.000	0.156	**0.222**	0.062	0.000	0.000	0.000	0.889
Customer Support	0.111	0.000	0.000	0.167	0.000	0.089	0.086	**0.139**	0.056	0.022	0.111	0.778
Development	0.050	0.000	0.000	0.050	0.033	0.040	0.011	0.033	**0.244**	0.140	0.100	0.700
QA	0.000	0.000	0.000	0.100	0.000	0.000	0.000	0.000	0.060	**0.300**	0.000	0.800
R&D	0.750	0.000	0.000	0.250	0.000	0.000	0.000	0.000	0.050	0.000	**1.000**	1.000
AI node	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	**0.000**

Source: calculated by the author using UCINET for Windows.

The cross-company comparison shows that the three organizations differ in the density of their communication networks but share a similar structural pattern. Mean intragroup density is consistently higher than mean intergroup density in all three organizations (Table 8). This suggests that direct communication ties are more concentrated within functional units than across their boundaries. The difference is most pronounced in Company A, where mean intragroup density reaches 0.457, compared with only 0.049 between functional groups. Companies B and C demonstrate the same structural pattern, although the difference between intragroup and intergroup density varies across the organizations.

Human-algorithmic interaction adds another dimension to this structure. Mean group-to-AI density reaches 0.874 in Company A, 0.731 in Company B, and 0.795 in Company C, substantially exceeding mean intergroup density in every case. This means that interaction with the AI node is widely distributed among functional groups even though direct communication between these groups remains comparatively limited. Employees from different functional areas can therefore interact intensively with the same digital node without being similarly interconnected through direct communication ties. This distinction shows that widespread human-algorithmic interaction can coexist with a communication structure that remains comparatively weakly connected across functional boundaries. Human-algorithmic interaction should therefore be considered alongside, rather than as an indicator of, cross-functional communication integration.

Table 8

Comparison of mean intragroup, intergroup, and group-to-AI density

Company	Mean intragroup density	Mean intergroup density	Mean group-to-AI density
Company A	0.457	0.049	0.874
Company B	0.252	0.095	0.731
Company C	0.513	0.064	0.795

Source: calculated by the author using UCINET for Windows and Excel.

From a management perspective, these results show that widespread interaction with AI should not be interpreted as an equivalent increase in organizational connectivity. Employees across functional areas may interact intensively with the same digital resource while direct communication between these areas remains limited. The management of human-algorithmic interaction therefore requires attention not only to the integration of AI into work processes but also to the existing communication structure and the channels through which information is exchanged across functional boundaries.

Conclusions. The study examined the structural characteristics of communication networks in product IT organizations by comparing intragroup, intergroup, and human-algorithmic interactions. The results show that these three dimensions are not equally represented within organizational communication networks. Despite differences between the analyzed companies, a common structural pattern can be identified.

First, communication is more intensive within functional groups than across their boundaries. Intragroup density varies considerably between functional units, indicating that internal communication is structured differently within the same organization. Some groups maintain dense networks with multiple direct communication ties, whereas others rely on a more limited set of relationships. At the organizational level, mean intragroup density is consistently higher than mean intergroup density in all three companies.

Second, intergroup communication is considerably more selective. Strong cross-functional relationships are present in each organization, but they are concentrated in particular directions and coexist with many weak or absent ties. Functional groups therefore form parts of the same organizational network without being equally connected to one another. Cross-functional information exchange may consequently rely more strongly on particular communication channels, distinguishing internal group connectivity from communication across functional boundaries.

Third, human-algorithmic interaction demonstrates a different structural pattern. Mean group-to-AI density is substantially higher than mean intergroup density in all three organizations. Employees from different functional groups can therefore interact intensively with the same digital node even when direct communication between those groups remains limited. The presence of AI across functional areas does not mean that AI structurally connects these groups. Instead, widespread human-algorithmic interaction coexists with communication networks in which direct ties remain more concentrated within functional groups than across their boundaries.

These findings demonstrate that human-algorithmic interaction and cross-functional communication represent distinct dimensions of the organizational network. From a management perspective, the extent of interaction with AI should therefore be considered together with the communication structure in which it occurs. Interaction with the same digital resource can be widespread across functional areas, while communication and coordination between these areas continue to rely on the interpersonal ties present in the organizational network. The management of human-algorithmic interaction should consequently consider both the integration of AI into work processes and the structure of communication across functional boundaries.

The study is limited to three product IT organizations and focuses on the structural characteristics of their communication networks. Future research should examine whether similar patterns are observed in larger samples and in organizations from other sectors. Longitudinal analysis could also clarify how intragroup, intergroup, and human-algorithmic interaction structures change as AI becomes more deeply integrated into organizational processes.

Declaration of AI use. ChatGPT (GPT-5.6 Sol,

OpenAI) was used for language editing, translation from Ukrainian into English, grammar and style checks, and assistance with literature search. The author reviewed and verified all AI-assisted content and takes full responsibility for the accuracy and integrity of the final article.

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