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A STUDY OF THE ROLE OF ARTIFICIAL INTELLIGENCE IN SHAPING HUMAN-ALGORITHMIC INTERACTIONS

ABSTRACT

This study examines the role of AI in shaping human-algorithm interaction (HAI) and determining its structural position within communication networks. The theoretical and methodological basis of the study includes social network analysis (SNA) and the principles of actor-network theory (ANT). Empirical data were collected through a survey of 145 specialists from three IT companies.

The results revealed structural changes in communication networks and transformations in interaction patterns among participants. The networks demonstrated low density, which can be explained by the integration of AI into organizational communication and the reduction of interpersonal connections. The findings show that AI has the highest in-degree centrality across all organizations and the highest reachability, based on its in-closeness centrality, indicating its strong structural influence within communication networks. Zero betweenness centrality values indicate that AI does not act as an intermediary agent and does not initiate communication. At the same time, information received from AI spreads through intermediaries within individual groups. No significant influence of AI on the geodesic distance metric was identified.

Analysis of behavioral patterns and motives for turning to AI revealed the formation of a hybrid task-allocation model. AI was predominantly used for creative and routine tasks, while social tasks were resolved through interpersonal interaction. An exception was observed in one company, where broader use of AI was noted even in social contexts. The choice of support sources was found to be selective by task type, with speed and experience dominating when turning to AI, and experience and reliability when consulting colleagues.

The findings demonstrate the evolutionary nature of HAI formation and show that AI integration changes not only technical processes but also the social logic of communication. Differences between companies reflect varying levels of digital maturity and confirm the active role of AI in the formation of hybrid socio-technical systems.

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

JEL Classification: M0, M1

INTRODUCTION

The integration of artificial intelligence technology is gradually moving from the realm of experimentation into the domain of everyday management practice. Today, algorithmic tools are being used for planning and coordinating work processes, supporting decision-making, interacting with customers, managing staff, and so on. In this context, the academic community is actively researching new project management strategies, leadership issues, the transformation of managerial competencies, impact on team productivity, and job satisfaction. The impact of artificial intelligence on employee productivity and overall organizational performance is demonstrated in the study by Kassa, B. Y., & Worku, E. K. (2025). It was found that employee productivity partially mediates the relationship between the implementation of AI and organizational effectiveness. The authors conclude that the integration of AI, combined with the creation of conditions favourable to increasing individual productivity, can significantly enhance organizations' competitive capabilities in the digital environment.

The study by Krakowski et al. (2025) shows that the effectiveness of interaction between humans and algorithmic systems in managerial tasks greatly depends on the alignment of this interaction with employees' individual cognitive styles. The authors note that a specially adapted interaction framework (procedures, authority, training, and incentives) boosts productivity, while inappropriate conditions lead to negative effects due to role ambiguity. The study's findings confirm the importance of a human-centered approach to AI implementation, which takes into account differences in employees' information processing and ways of thinking.

The study by Ateeq et al. (2025) emphasizes that AI is also capable of increasing employee engagement and productivity by optimizing workloads and supporting managerial decisions. Meanwhile, the authors draw attention to a number of risks associated with the integration of AI into the work environment. These include a decline in organizational trust, a lack of transparency in algorithmic decisions, and a potential deterioration in the quality of interaction between employees and employers. The study also emphasizes the need for ethical AI governance and leadership approaches capable of striking a balance between technological advantages and the maintenance of sustainable forms of professional interaction.

A number of recent academic works describe artificial intelligence as a catalyst for significant transformations in leadership and management. Joshi S. (2025) emphasizes in his study that the integration of AI modifies leadership styles and transforms decision-making processes in the digital environment. These changes present organizations with new challenges related to cultural adaptation and ethical responsibility. Other researchers offer a conceptual model where leadership plays a key mediating role in the interaction between human and artificial intelligence. According to Zárate-Torres et al. (2025), it is precisely leadership mechanisms that ensure the ethical governance of AI systems, maintain a balance between algorithmic efficiency and human cognitive adaptability, as well as determine the principles of human control over automated processes. From this perspective, leadership emerges as a dynamic facilitator of human-algorithm interaction, creating the conditions for flexible, responsible, and reasoned strategic decision-making.

Despite the rapid spread of algorithmic systems in the field of management, the academic discourse remains theoretically fragmented. A study by Hillebrand et al. (2025) indicates that human-algorithm interaction in management is shaped by two previously separate approaches, "human-AI collaboration" and "algorithmic management", which in fact describe complementary aspects of a single process. The authors integrate these approaches and prove that AI-assisted management must be analyzed at the organizational system level, where agency, context, and the consequences of interaction become collective in nature. The proposed integrative framework lays the groundwork for the development of a comprehensive theory of management amid the growing role of algorithmic systems.

Considering the theoretical fragmentation of the discourse and the emergence of integrative approaches in management, empirical research into how human-algorithm interactions actually develop within organizational systems becomes crucial.

In this article, we take the assumption that a deep understanding of relational processes within an organization is a prerequisite for the reasoned definition of management models in a hybrid environment. The present study identifies existing gaps in the scientific discourse and proposes an approach that makes it possible to study human-algorithm interactions in the digital environment of IT organizations substantively. Apart from summarizing the current state of scientific research in the field of management, this study presents comprehensive empirical research covering:

- analysis of hybrid communication networks based on structural indicators;
- analysis of the position of AI within the overall structure of IT organizations' communication networks;
- analysis of the dissemination of information received from AI via intermediaries;
- analysis of the frequency with which respondents turn to artificial intelligence,
- analysis of the nature of respondents' interactions with AI and colleagues across different types of tasks;
- analysis of the reasons respondents turns to AI and colleagues.

The proposed approach makes it possible to move from conceptual considerations regarding the role of artificial intelligence in management to an empirically grounded analysis of how hybrid communication networks emerge and how the structure of organizational relationships changes under the influence of digital agents.

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LITERATURE REVIEW

The authors conducted a quantitative analysis of scientific articles in the international scientometric databases Web of Science and Scopus in order to assess the overall state of research in the field of artificial intelligence. Analysis results for the "Author keywords" Artificial Intelligence parameter in the Web of Science database revealed a high level of academic interest in this subject, as evidenced by the presence of 84,100 scientific articles. An analysis of the distribution by discipline demonstrates a significant dominance of technical disciplines. The largest number of works is concentrated in the Engineering Electrical Electronic (17,252 articles), Computer Science Information Systems (16,124 articles), and Computer Science Artificial Intelligence (13,988 articles) categories. A significant proportion of research is also represented in the Computer Science Interdisciplinary Applications category (10,393) and the Computer Science Theory Methods category (8,847 articles). Compared to the leading technical fields, the Management category is represented by only 3,191 publications.

Within the Management category, a search was also conducted using more specialized queries. In particular, the query "Human-AI Collaboration" revealed 7 publications, "Hybrid Intelligence" – 10, "Human-algorithm interaction" – 0, and the keyword "algorithmic management" – 29 publications (Web of Science (n.d.)).

An additional search in the Scopus database using the "Keywords" criterion with the term "Artificial Intelligence" revealed 215,851 scientific publications. The distribution of publications by subject area confirms the dominance of the technical sciences. The largest number of articles belongs to the Computer Science category (95,140 articles) and Engineering (62,211 articles). A significant number of studies were found in the fields of Medicine (47,509 articles), Mathematics (28,314 articles), and Social Sciences (26,593 articles). Meanwhile, the Business, Management, and Accounting category comprises only 11,376 publications, which is a notably lower figure compared to the leading fields. To clarify the internal structure of research in the field of management, we also conducted an additional search using specialized queries. In particular, the query "Human AI Collaboration" revealed 31 publications, "Hybrid Intelligence" – 7, "Human-algorithm interaction" – 7, and the keyword "Algorithmic management" – 59 publications (Scopus (n.d.).

An analysis of the overall state of scientific research shows that issues concerning human-AI interaction in the field of management remain underdeveloped. Furthermore, the pace of theoretical reflection on the role of AI in the sector does not match the speed of its development and implementation in organizational processes. As the integration of AI as a technological system is becoming a critical condition for the competitiveness of modern business, further research in this field is essential. This will enable a deeper understanding of the transformations in management practices and changes in organizational interaction arising from the integration of algorithmic tools.

The role of artificial intelligence in shaping human-algorithm interaction is a subject of current academic research. The scope of this research is gradually expanding from philosophical reflections on the nature of technology to comprehensive interdisciplinary approaches. Currently, this issue encompasses economic, social, ethical, legal, psychological, and management aspects. Specifically, the theoretical and applied aspects of this topic are studied in the scientific works of Sowa K., Przegalinska A., Ciechanowski L., Sundar S. S., Raisch S., Fomina K., Meijerink J., Keegan A., and others. These researchers study models of interaction between humans and AI tools and analyze the risks associated with such collaboration. They pay particular attention to the potential for cooperation in mixed teams, as well as issues of hybrid management and delegating functions to digital agents. Their works also examine the conditions for building trust in algorithms, the transformation of organizational roles, and the socio-technical changes that arise during the integration of AI into management processes. Jarrahi et al. (2021) examine algorithms as socio-technical mechanisms that transform power relations between employees and managers and alter the distribution of competences within organizations. As a result, algorithms serve not only as instruments of control but also as institutional participants in management. Beckers and Teubner (2023) analyze issues of social and legal responsibility in the interaction between humans and algorithmic systems. The researchers suggest considering such configurations as quasi-organizations, within which responsibility and accountability are shared between human and non-human agents. Based on actor-network theory and systems theory of organizations, the authors demonstrate that algorithms, whilst remaining technical systems without consciousness, can acquire social agency as "actants" in legal and communicative processes. As a result, such hybrid associations emerge as digital collective actors that function as elements of contemporary social institutions and require new models of collective responsibility.

Contemporary research into human-AI interaction also covers cognitive, social, and cultural-communicative domains. Within these areas, human and AI co-participation in processes of thinking, creativity, and communication is analyzed. Research by Fedorets et al. (2024) shows that interaction with artificial intelligence transforms the human cognitive domain and can be considered a special form of partnership in cognitive activity. Within the "human–AI" system, a complex multi-channel cognitive system is formed, in which analytical, interpretative, and creative functions are distributed between human and algorithmic agents.

Peeters et al. (2021) provided a conceptual framework for understanding the interaction between humans and artificial intelligence. In their "Human–AI Society" model, they identify three analytical perspectives: technology-centered, human-centered, and collective intelligence-oriented. The technology-centered perspective is based on the assumption that AI will become a highly developed system capable of surpassing human cognitive capabilities. The human-centered perspective emphasizes the uniqueness of human intelligence, grounded in moral judgment, empathy, and cultural experience, which remain beyond the reach of artificial systems. The collective intelligence-oriented perspective views intelligence as a property of a network of interactions between many agents, where cognition, understanding, and decision-making are the result of the joint activity of humans and AI. It is exactly this perspective that allows us to interpret contemporary society as a "Human–AI Society".

A significant contribution to research on the social nature of artificial intelligence was made by Pîrjan and Petroşanu (2025). The researchers view Artificial Social Intelligence (ASI) as a key factor in the transformation of modern communication. The authors argue that algorithmic agents can participate in social processes, recognize human emotional states, adapt their own behaviour, and influence cognitive and emotional reactions. This results in the formation of a hybrid "human-algorithm" social space, which requires new approaches to ethical, cultural, and regulatory governance.

The concept of distributed cognition, proposed by Hollan, Hutchins, and Kirsh (2000), provides an important theoretical foundation for comprehending human-algorithm interaction. According to this approach, cognitive activity is viewed not as a purely internal process, but as one that is shaped through human interaction with external artefacts, tools, and the social context. The authors demonstrate that cognition exists as a network of coordinated actions, where tools function as active elements of the cognitive system. In this sense, modern algorithms and artificial intelligence systems can be viewed as an extension of the human cognitive environment, as they are involved in structuring tasks, supporting decision-making, and influencing the course of collective processes. This perspective allows us to interpret human-algorithm interaction as a form of distributed cognitive activity, within which intellectual functions arise in a shared "human-digital tool" system.

The philosophical dimension of the problem of the coexistence of humans and artificial intelligence is analyzed by Petrunko and Pliushch (2025). The researchers substantiate a meta-subjective paradigm of cognition, which rejects the notion of artificial intelligence as an autonomous subject. In contrast to approaches that recognize the agency or social agency of AI, this approach treats it as a cognitive tool that expands the capabilities of human thought, communication, and self-reflection. Humans remain the sole bearers of meaning, values, and moral responsibility. Artificial intelligence, meanwhile, performs a supporting role in the process of cognition and social interaction.

In academic discourse, the issue of artificial intelligence consciousness remains a subject of significant theoretical disagreement. Although some researchers acknowledge the possibility of AI developing cognitive characteristics similar to human consciousness, the literature contains compelling arguments that cast doubt on such assumptions. In particular, the theoretical and hypothetical work by Guingrich and Graziano (2024) demonstrates that the human tendency to attribute consciousness to artificial intelligence is a consequence of certain psychological mechanisms. The authors explain that people interpret the behaviour of technological systems through existing mental models, which were originally formed to recognize the intentions and emotions of other people. When an algorithmic agent demonstrates human-like linguistic or behavioural responses, the subject activates established cognitive mechanisms for interpreting social behaviour. It is precisely this that may lead to the interpretation of artificial intelligence behaviour as being grounded in internal mental states. The study emphasizes that such attribution does not indicate the presence of consciousness in artificial intelligence, but reflects the peculiarities of human perception. This provides grounds for considering the anthropomorphization of AI as a cognitive phenomenon that cannot serve as evidence of the subjectivity or autonomous thinking of digital agents.

An analysis of scientific sources shows that approaches to studying the interaction between humans and artificial intelligence remain theoretically heterogeneous and methodologically fragmented. Some researchers view AI as an active participant in social and organizational processes. Others emphasize that it is merely a tool that expands the capabilities of human cognition. There also remain significant disagreements regarding the level of autonomy, agency, and possible signs of consciousness in artificial intelligence.

Such contradictions complicate the formation of a coherent understanding of how the integration of AI is changing the structure of social interaction within organizations. Most studies focus on theoretical models of human-algorithm interaction, yet the actual transformations of communication processes in the digital environment are scarcely explored. Contemporary literature also lacks studies documenting the actual configurations of relationships between human and digital

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agents. This limits the possibility of a full understanding of how the integration of AI alters the nature of interactions, influences the redistribution of roles, and affects the circulation of knowledge within an organization.

To investigate the role of artificial intelligence in shaping human-algorithm interaction, it is appropriate to turn to Bruno Latour's Actor-Network Theory (ANT). Latour, together with Callon and Law, laid the foundations for a systematic comprehension of the agency of technological systems and their impact on social processes. Within ANT, the traditional distinction between the natural and social worlds is rejected; instead, reality is viewed as a hybrid network of interactions (Latour, 1993). According to ANT, people, technologies, objects, and institutions jointly shape socio-technical processes. In this paradigm, interaction is not a purely human activity, as non-human agents are capable of initiating actions, influencing the course of events, and altering the structure of network connections (Nickerson, 2024).

Latour's ideas remain particularly relevant today and provide a methodological foundation for further analysis of algorithmic systems as active components of social reality. That is why, in this article, the role of artificial intelligence is explored by combining the conceptual provisions of actor-network theory with the application of social network analysis (SNA) methodology. This approach enables an empirical investigation of the configuration of human-algorithm interactions within the communication networks of IT organizations.

AIMS AND OBJECTIVES

The aim of the study is to determine, both theoretically and empirically, the role of artificial intelligence in shaping human-algorithm interaction. To achieve this objective, the study aims to address the following scientific tasks:

1. To conduct a systematic review of current scientific research examining the role of artificial intelligence in social and organizational processes.
2. To apply social network analysis (SNA) methodology to identify the impact of AI on the structural parameters of communication networks.
3. To determine the structural position and functional role of AI in the communication networks of IT organizations.
4. To identify the motives for employees turning to various sources of support and to assess the factors influencing the acceptance of AI as a partner for joint activities.
5. To identify the features of the formation of socio-digital connections in the communication networks of product IT organizations.

METHODS

Social Network Analysis (SNA) was employed to study sociocentric, directed, and asymmetric communication networks. The theoretical framework was based on the works of Freeman (1979) and Borgatti, Everett, and Freeman (2002). Empirical data were collected from three product IT organizations using an online survey. A total of 145 IT specialists were surveyed, comprising 42 employees from Company A, 49 from Company B, and 54 from Company C. The survey questions comprised four blocks of situational tasks: 1) functional tasks, 2) social tasks, 3) creative tasks, and 4) routine tasks. To solve the situational tasks, respondents selected a specific source of assistance. The available sources were either colleagues or artificial intelligence tools. In their responses, respondents could name only one colleague or AI. Additionally, participants rated the frequency of their interactions with the chosen source of assistance on a six-point scale, where 1 point indicated no interaction, and 6 points reflected daily communication and a high level of engagement. The proposed scale format is a type of intensity scale used to record the frequency of behavioural manifestations. Each value on the scale represents an independent quantitative assessment of the frequency of interaction, rather than being formed as an integral indicator based on a set of statements requiring verification of internal consistency. Consequently, a separate "Likert scale validation" procedure was not applied.

After cleaning and anonymizing the respondents' personal data, binary and valued adjacency matrices were generated. The resulting binary matrices recorded the presence of a directed tie between network nodes, whilst the valued matrices captured the intensity of interaction based on the frequency of requests. The matrices included respondents who had not completed the questionnaire, but were mentioned in the questionnaire by other respondents. Artificial intelligence was also added as a separate element, functioning as a digital node in the communication network.

The analytical stage of the study involved the calculation and interpretation of key network indicators, specifically geodesic distance, density, degree centrality, betweenness centrality, and closeness centrality. The selection of these network indicators is based on their ability to reflect various and interrelated aspects of the network structure and the roles of individual participants. The indicators were calculated using the UCINET for Windows software, and the communication networks were visualized using NetDraw software (Borgatti, Everett, and Freeman, 2002). To ensure comparability of networks of different sizes, selected indicators were normalized or standardized using appropriate procedures.

Based on the data obtained, a comparative analysis of the communication networks of product IT organizations was conducted using structural indicators. The analysis of network indicators made it possible to assess the spatial organization of interactions between nodes, the level of overall network connectivity, the influence of the AI node, its participation in the formation of information flows, and accessibility to other network participants. The approach employed made it possible to comprehensively describe the configuration of communication ties in product IT organizations and to identify the features of human-algorithm interaction.

In addition to analyzing communication networks, the study examined the motives that determine the choice of a specific source of assistance. A comparative analysis of behavioural patterns was conducted based on respondents' answers regarding the reasons for turning to one source or another. Four key motives were identified: accessibility, reliability, experience, and speed of assistance. Analysis of these motives made it possible to compare the advantages respondents associate with human and digital participants in the interaction. Furthermore, it made it possible to understand which factors influence the perception of artificial intelligence as a partner within work communications.

RESULTS

Within the framework of this study, a comparative analysis of the communication networks of three product IT organizations was conducted. The application of social network analysis (SNA) methodology made it possible to identify the characteristics of the formation of informational ties in human-algorithm interactions, as well as to investigate structural changes in the organizations' communication networks. To ensure the comparability of networks of different sizes, all indicators were standardized.

Structural analysis of the networks was carried out using key indicators such as geodesic distance, density, degree centrality, betweenness centrality, and closeness centrality. The results allowed us to identify the characteristics of communication network formation in the organizations under study and to determine the influence of the artificial intelligence node (AIN) on the structural distribution of information flows, the configuration of network connections, and the nature of interactions between participants.

Analysis of geodesic distance

A comparative analysis of geodesic distance made it possible to estimate the average number of intermediaries involved in the transmission of information, as well as to determine the speed and efficiency of internal communication. Lower values of this indicator indicate fewer intermediaries between network participants and shorter paths of information exchange. To ensure a fair comparison of networks of different sizes, this metric was standardized by dividing the average geodesic distance by the natural logarithm of the number of nodes (Kastrin et al., 2014).

The results showed that Company B's network is the most compact (0.60), ensuring faster transmission of information. Company A has a geodesic distance of 0.73, and Company C has a geodesic distance of 0.83 (Table 1).

Table 1. Comparative analysis of average geodesic distances in the IT companies studied.

Company	Number of nodes in the network	Average geodesic distance	Natural logarithm of the number of nodes	Normalized value of the average geodesic distance
Company A	43	2.744	3.76	0.73
Company B	50	2.340	3.91	0.60
Company C	55	3.340	4.01	0.83

This indicates a greater number of intermediate ties and lower efficiency of information circulation. Overall, the communication networks in all three organizations demonstrate moderate average path lengths between nodes (Freeman, 1979; Borgatti, Everett, and Freeman, 2002; Humphries and Gurney, 2008; Watts and Strogatz, 1998; Wasserman and Faust, 1994). Weakly integrated nodes in communication networks potentially reduce the flexibility of information exchange, slow

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down collective decision-making, and increase the risk of network fragmentation. Managers should focus on strengthening horizontal ties to improve the effectiveness of communication and knowledge sharing within the organization.

Analysis of the density index

An analysis of the network density index allowed us to assess the degree of structural integration and the intensity of information exchange within each of the IT companies studied. The density index reflects the proportion of actual ties to the maximum possible number of ties in the network. The higher the density value, the greater the proportion of existing ties and the higher the level of overall network cohesion (Oliveira and Gama, 2012). Z-standardization was applied to facilitate the comparison of relative differences in density values across networks and to highlight deviations from the mean density level.

Among the companies studied, the highest network density was recorded in Company A (1.40). Company B has a density value of -0.89, whilst Company C has a value of -0.51 (Table 2). Meanwhile, in all three organizations, the density level is low, which may be indicative of isolated subgroups, insufficient team integration, and a slower exchange of knowledge (Derr, 2024).

Low-density figures can also be explained by the presence of an AIN, which concentrates a significant proportion of information requests around itself. Consequently, this leads to fewer interpersonal connections and reduces the overall density of the network's communication structure. Managers should note that such a structure limits the flexibility of internal communications and complicates the rapid coordination of joint activities.

Table 2. Comparative analysis of density indices.

Company	Number of nodes in the network	Network density	Mean density	Squared deviation	Variance	Standard deviation	Z-score
Company A	43	0.107	0.089	0.0003	0.0002	0.013	1.40
Company B	50	0.077		0.0001			-0.89
Company C	55	0.082		0.0000			-0.51

In addition to analyzing the overall network density, the study also examined density metrics within individual groups and between groups within the organization. These results are not included in the article, as this work focuses primarily on the global characteristics of the networks under study. However, the results obtained can serve as a basis for analyzing internal structures, forming team management strategies, and improving the effectiveness of interpersonal relationships within the organization.

Analysis of network centralization

An analysis of the network's global centralization allowed us to assess the extent to which communication flows within organizations are concentrated around individual key participants. High centralization values indicate that a significant portion of information passes through a few dominant nodes. Such a structure may facilitate rapid decision-making, but at the same time, it reduces the flexibility of the network and increases dependence on central elements (Hanneman and Riddle, 2005).

Standardized values of Freeman's global centralization index were used for comparative analysis. These values were obtained during the calculation in the UCINET for Windows software. As the networks under study were directed, calculations were performed separately for the In-Degree and Out-Degree centralization indices (Lizardo, 2020).

The analysis showed that the value of out-degree centralization is highest in Company A (0.158) compared to Companies B (0.067) and C (0.105). This indicates that Company A has individual nodes that initiate outbound communications and direct information flows to other network participants (Table 3). However, it is worth noting that the out-degree centralization values are low in all three companies. This is typical for networks in which most participants rarely initiate outbound communication, so information flows are distributed relatively evenly across the network. It also explains the absence of clearly defined centers of communication initiation.

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Table 3. Comparative analysis of Freeman's global centralization index.

Company	Out-Degree	In-Degree
Company A	0.158	0.743
Company B	0.067	0.733
Company C	0.105	0.728

High values of in-degree network centralization were recorded for all three companies. Specifically, Company A has a value of 0.743, Company B – 0.733, and Company C – 0.728. This indicates the presence of leading nodes that play a key role in the accumulation and distribution of information, functioning as the main points for receiving requests from other participants. The study also found that the AIN node has the highest values of the In-degree centrality in all three companies (Table 4). This indicates that the integration of AI into the organization's network influences and alters the configuration of communications within the social system. Thus, the digital agent occupies the position of an influential node, which other network participants most frequently turn to for information or support.

Table 4. Comparative analysis of the AIN node's degree centrality. *(Source: Estimated using UCINET software)*

Company	Out-degree	In-degree
Company A	0.00	35.00
Company B	0.00	39.00
Company C	0.00	43.00

Managers should take into account that a high level of in-degree centrality increases the organization's dependence on a limited number of key nodes, particularly the AIN digital agent. When it is overloaded or experiences technical failures, the network's communication resilience may be significantly reduced. For this reason, it is advisable to develop additional channels for knowledge exchange among employees and to maintain a more even distribution of information flows, in order to avoid excessive concentration on a single digital hub.

Analysis of betweenness centrality

An analysis of global betweenness centrality using Freeman's method revealed the degree of influence of individual nodes on the organization of information flows and the level of intermediation within networks. This metric allows the identification of individual nodes that act as intermediaries in communication, i.e., serve as important "bridges" for the transmission of information between other network participants (Oliveira and Gama, 2012).

The comparative analysis utilized standardized betweenness centrality values, which were calculated using the UCINET for Windows software. These values are presented in numerical format, which facilitates the interpretation and comparison of the results obtained.

The calculations showed that Company C has the highest betweenness centrality (0.46), meaning that its structure contains clearly pronounced intermediary nodes that function as the network's main "bridges." The network paths in companies A (0.19) and B (0.08) are distributed more evenly, with no concentration of flows around individual participants (Table 5). Such a network is more flexible and less dependent on individual nodes; however, under complex conditions, a reduction in the efficiency of information exchange and coordination of actions may occur.

Table 5. Comparative analysis of the Freeman centrality index. *(Source: Estimated using UCINET software)*

Company	Network centrality index, %	Network centrality index
Company A	19.86%	0.19
Company B	8.12%	0.08
Company C	46.14%	0.46

It is worth noting that in all three companies, the AIN node has a zero betweenness centrality value (Table 6). This indicates that the AIN node does not occupy intermediary positions on the shortest paths between other nodes.

Table 6. Comparative analysis of the AIN nodes' betweenness centrality. *(Source: Estimated using UCINET software)*

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Company	Normalized betweenness score (nBetweenness)
Company A	0
Company B	0
Company C	0

Managers should note that high betweenness values increase the organization's dependence on individual intermediary nodes. On the one hand, such a network configuration ensures rapid coordination of actions and maintains the overall integrity of the network. On the other hand, it creates risks in the event of intermediary nodes becoming overloaded or leaving the organization's network. Companies with a more even distribution of intermediary functions have no need to further increase the number of communication "bridges" in the network.

Analysis of closeness centrality

Analysis of closeness centrality enabled us to assess the degree of information accessibility (reachability) of participants within the networks under study. This metric reflects the relative closeness of a node to other nodes in the network based on the length of the shortest directed paths (Gómez, 2019). High values of this index indicate a compact information space, increased communication efficiency, and the organization's ability to respond quickly to changes (Kim, 2019).

Normalized values of the closeness centrality index, calculated using the UCINET for Windows software, were used to conduct a comparative analysis. As this indicator was calculated for each node individually, the median value of the normalized indicators of InCloseness centrality and OutCloseness centrality was calculated to determine the overall level of network closeness.

The comparative analysis revealed that Company A has the highest values for out-closeness (0.250) and in-closeness (0.256) centrality among the organizations studied. Such a network structure indicates a high level of information accessibility of nodes and the efficiency of internal information exchange compared to other companies. For example, companies B (0.163; 0.126) and C (0.174; 0.198) recorded lower scores for both in- and out-closeness (Table 7). This indicates greater information distances between nodes and slower circulation of information within the network. Overall, all three organizations have moderate closeness centrality indicators, which may be explained by the presence of broken ties or a fragmented communication network structure.

Table 7. Comparative analysis of the median of normalized closeness.

Indicator	Company A	Company B	Company C
Out-closeness centrality (OutClose)	0.250	0.163	0.174
In-closeness centrality (InClose)	0.256	0.126	0.198

The analysis also confirmed that AIN has the highest values for the in-closeness centrality (Table 8). This indicates that the AIN node is highly reachable within the communication structure. It is situated within the communication structure in such a way that most participants can quickly access it. This structural configuration enhances its influence and importance for information exchange and the support of organizational processes.

Table 8. Comparative analysis of the AIN node's closeness index. *(Source: Estimated using UCINET software)*

Indicator	Company A	Company B	Company C
Out-closeness centrality (OutClose)	0.125	0.125	0.091
In-closeness centrality (InClose)	0.494	0.590	0.370

Managers should take into account that a high degree of connectivity between nodes in a network facilitates the rapid exchange of information and enhances the organization's ability to respond promptly to changes. To maintain such a structure, it is advisable to regularly analyze the presence of fragmented or isolated sections of the network that slow down the circulation of knowledge. Strengthening horizontal ties helps to reduce information gaps, thereby improving the overall effectiveness of organizational interaction.

Analysis of the frequency of AI use

An analysis of the average frequency of artificial intelligence technology use revealed significant differences in the level of digital maturity among the companies studied. Z-standardization was applied to clarify these differences and ensure a correct comparison of indicators. As a result of the analysis, the highest indicator was recorded for Company A (1.40). This demonstrates the deep integration of AI into business processes and its systematic use to enhance the efficiency of organizational activities (Table 9). It was found that Companies B (-0.60) and C (-0.80) have standardized values below average. This indicates a limited level of AI usage by employees. This situation is partly explained by the fact that both companies started integrating AI only in 2023. The results may also be associated with limited resources, a lack of necessary skills among employees, and a lack of readiness for technological change. According to the results, Company A, which integrated AI in 2022, has achieved the highest level of digital maturity and demonstrates the most consistent use of innovation among the organizations under study.

Table 9. Average frequency of AI use in product IT organizations.

Company	Average frequency of AI use	Mean value	Squared deviation	Variance	Standard deviation	Z-score
Company A	5.00		0.08			1.40
Company B	4.60	4.72	0.01	0.04	0.20	-0.60
Company C	4.56		0.03			-0.80

Analysis of the position of AIN within the overall structure of communication networks

Analysis of the AIN node within the communication network structure of Company A showed that AI occupies a central position (Figure 1). This structural position defines its role as a key digital actor in the interaction. The graphical network model demonstrates that the largest proportion of information contacts is directed towards AIN.

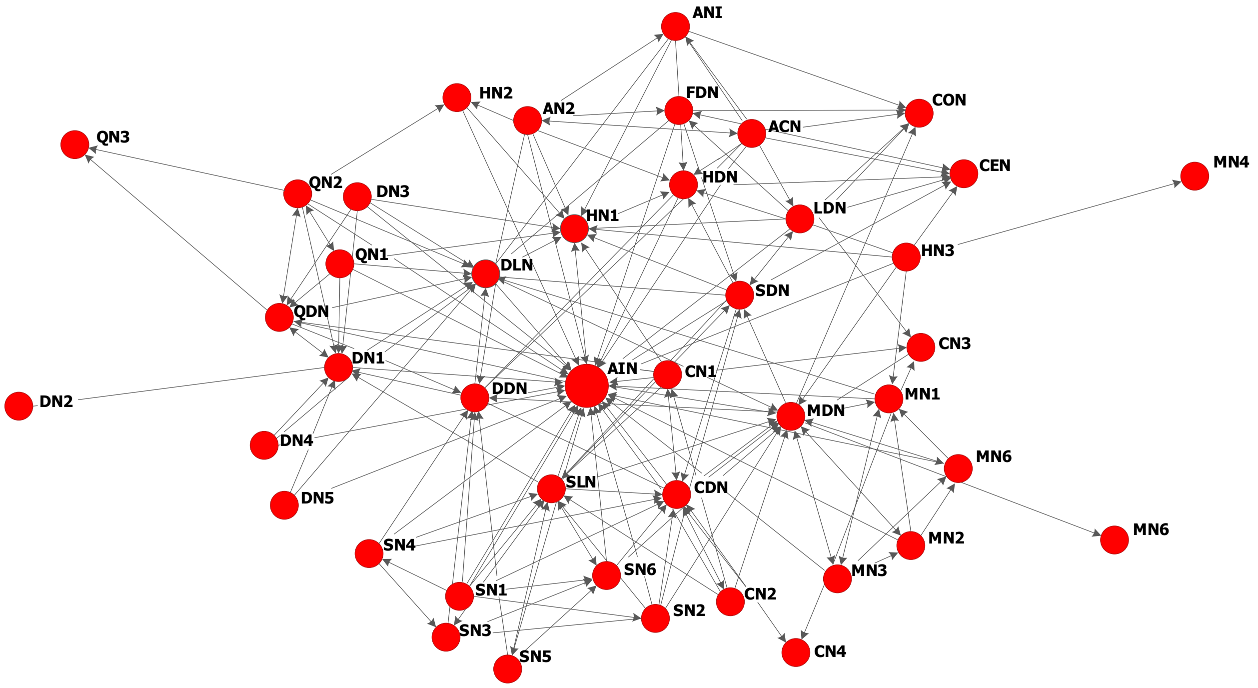

Figure 1. The position of AIN within the overall structure of Company A's communication network. *(Source: Created using NetDraw software)*

This structurally influential position of AIN is also confirmed by the node's maximum in-degree centrality and closeness measures among all network participants. This configuration indicates the AIN node's ability to accumulate requests, provide rapid access to information resources, and influence the organization of internal information flows. In Company B's communication network, the AIN node also acts as a powerful hub for digital interaction. Its structural function differs from that in Company A's network in that AIN is involved in a more extensive and balanced system of request exchange

(Figure 2). A large number of employees from various clusters submit information requests to AIN, which ensures it achieves the maximum values for the indicators of in-centrality and closeness. At the same time, a fairly well-developed system of interpersonal connections between employees is evident in Company B's network.

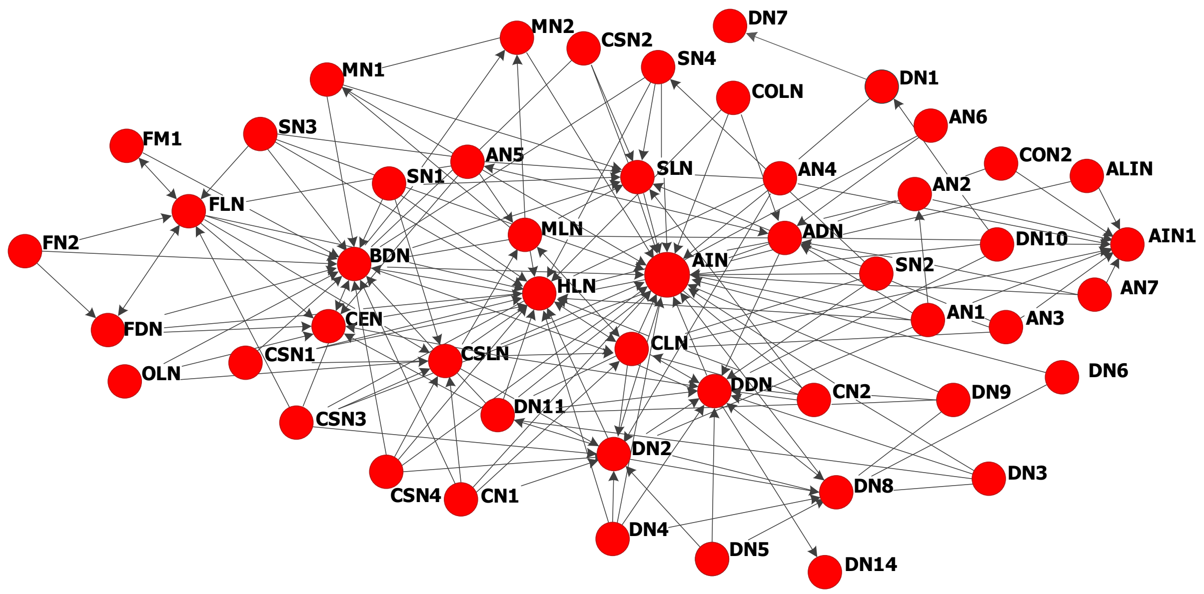

Figure 2. AIN's position within the overall structure of Company B's communication network. *(Source: Created using NetDraw software)*

The graphical model of Network B also shows that information exchange is not centralized around a single AIN node, but retains a differentiated structure. Despite its dominant position, the AIN node is not the organization's sole information hub. Under these conditions, its function is to support digital communication processes, which do not exclude traditional interpersonal channels of interaction.

In Company C's communication network, the AIN node also occupies a central position (Figure 3). However, the structure of interaction demonstrates a unique balance between digital and social flows. AIN accumulates requests from employees across various departments, which ensures high levels of in-centrality and closeness. At the same time, the graphical visualization of the network shows a branched system of connections between individual groups that maintain communication independently of the central digital node.

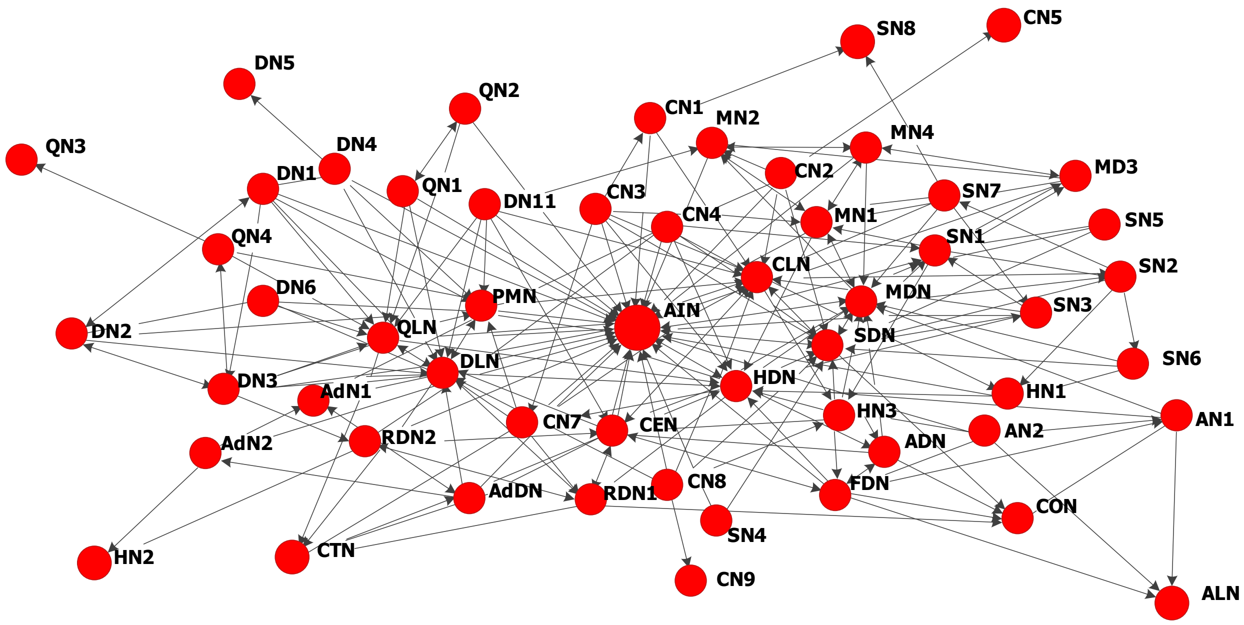

Figure 3. The position of AIN within the overall structure of Company C's communication network. *(Source: Created using NetDraw software)*

Within Company C's network, the AIN node acts as a key digital information hub, but does not monopolise the distribution of communication flows. The structure of interaction preserves multi-channel communication and differentiated social ties between employees. Thus, the AIN node in Company C supports digital communications but does not replace the social foundation of organizational interaction.

Overall, Figures 1, 2, and 3 demonstrate the general topology of communication networks based on empirical data. The models record only the fact of the existence of a connection, without taking into account additional attributes or qualitative characteristics of interaction. The spatial arrangement of nodes provides an idea of the general configuration of the network. The direction of the arrows reflects information flows between nodes, allowing the identification of sources and recipients of information.

Analysis of the dissemination of information received from the AIN node via intermediaries

Figures 4, 5, and 6 depict a graphical model of information dissemination received from the AI via intermediary nodes. The network model is based on the responses of participants who indicated that they pass on information received from AIN to other members of the communication structure. Within Company A's network, the dissemination of information from the AIN node via intermediaries forms a clearly defined radial structure (Figure 4). The graphical model demonstrates that, following an initial contact with AIN, individual employees pass on the information received to their colleagues. Thus, secondary communication chains are formed.

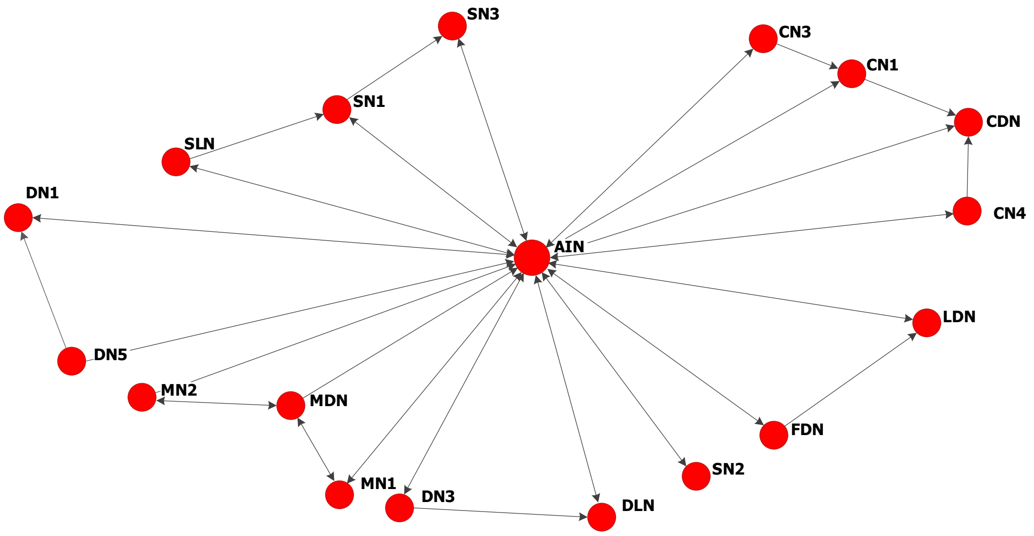

Figure 4. A graphical representation of how information spreads from the AI node via intermediaries within Company A. *(Source: Created using NetDraw software)*

An analysis of information dissemination indicates that the digital agent acts as a key source of information flows within Network A. At the same time, the further diffusion of knowledge depends on employees' individual decisions and on the intensity of internal social contacts. In other words, AIN initiates the exchange process, but its development is determined by interpersonal relationships within the organization.

A typical configuration for Network A is local exchange within small subgroups. The intermediary node shares the information received with a limited circle of colleagues, which results in a relatively fragmented structure. Although the AIN accumulates a significant number of requests, the further dissemination of knowledge remains localized and does not cover the entire organizational network.

The communication network of Company B also retains a radial structure in the dissemination of information from the AIN node via intermediaries. At the same time, more secondary information transmission chains are formed within it (Figure 5). The graphical model shows that some employees, having received information from the AIN, pass it on to colleagues, forming short sequential ties between network participants.

Within the subgroups of Network B, employees actively participate in disseminating the information received. This creates additional communication ties and broadens the circle of staff who have access to the knowledge generated by the digital agent. The secondary transmission of information becomes a defining feature of these local groups and indicates a higher level of employee engagement in knowledge sharing.

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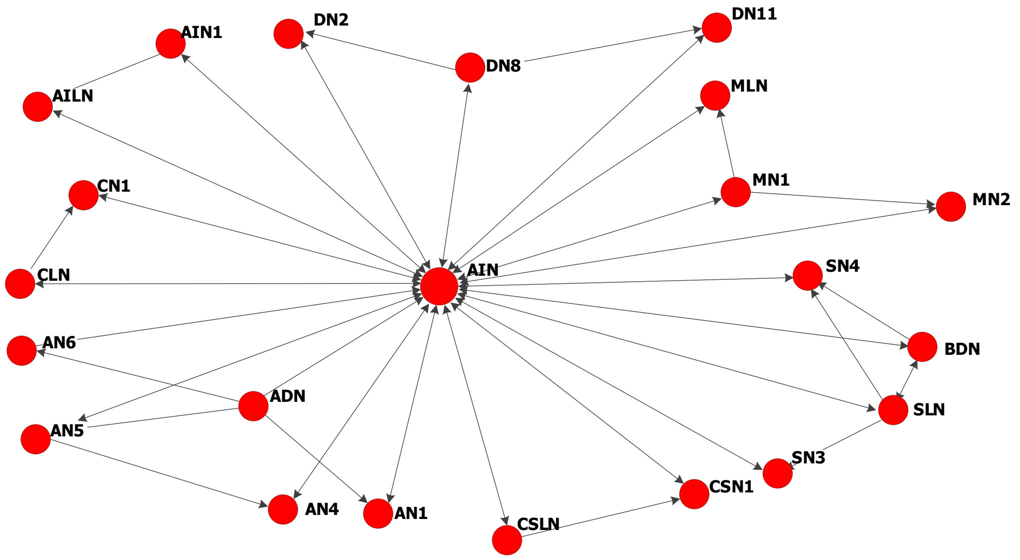

Figure 5. Graphical representation of how information spreads from the AI node via intermediaries within Company B. *(Source: Created using NetDraw software)*

Despite the active circulation, the network structure remains relatively localized. Knowledge dissemination largely takes place within individual groups and does not cover the entire network. Thus, the secondary dissemination of information in Company B is more intensive, yet its scope remains limited.

Within Company C's network, the dissemination of information from the AIN node via intermediaries is the most extensive among the networks studied (Figure 6). The graphical model shows that, after receiving information from AIN, individual employees actively pass it on, forming a network of interconnected contacts between different subgroups.

It also shows that information from AIN spreads not only directly but also through several successive stages. Some employees pass on information to their colleagues, forming longer communication chains. This mechanism ensures that different departments are covered and enhances the open exchange of knowledge within the organizational structure. This configuration defines the network as more dynamic, facilitating more effective circulation of information among participants. In this model, the AIN functions as the starting point of subsequent information dissemination, whereas its further circulation depends on interpersonal communication between employees. This allows a wider segment of the network to be covered and ensures the rapid dissemination of knowledge within the organization.

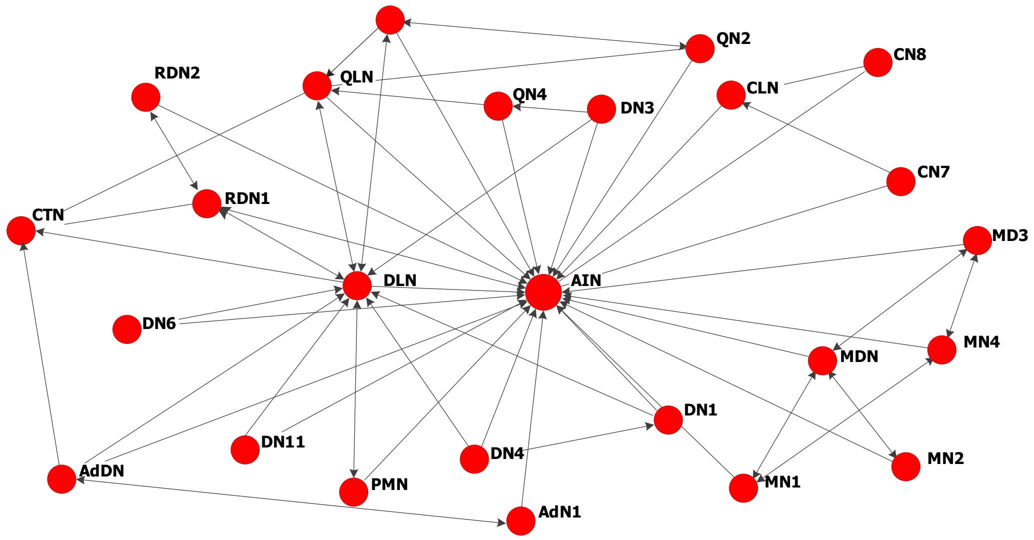

Figure 6. Graphical representation of how information spreads from the AI node via intermediaries within Company C. *(Source: Created using NetDraw software)*

The aggregated results show that the dissemination of information from the AIN node takes the form of a multi-level process combining centralized and decentralized exchange mechanisms. It was established that the AIN acts as the primary source of knowledge; however, the subsequent circulation of information depends on the activity and decisions of employees. In all of the companies studied, information received from the AI spreads mainly within small local groups. Such clusters form around employees who regularly interact with one another or perform related functions. In more structurally complex networks, these local exchanges encompass a wider circle of employees, forming more diversified knowledge transfer pathways. Overall, the dissemination models demonstrate a combination of digital and interpersonal channels. The AIN node initiates information flows, and their subsequent circulation depends on the level of internal communication and the culture of knowledge sharing.

Nature of respondents' interactions with AI and colleagues across different types of tasks

A comparative analysis of patterns of engagement with different support sources revealed both similarities and differences. The study's findings show that at Company A, employees rely on AI for assistance significantly more often than on advice from colleagues. Even when performing social tasks that traditionally require interpersonal interaction, the number of requests to AI significantly exceeds the number of consultations with colleagues (Figure 1). This pattern of behaviour may reflect a high level of digital adaptability and an established digital culture of interaction with algorithmic agents.

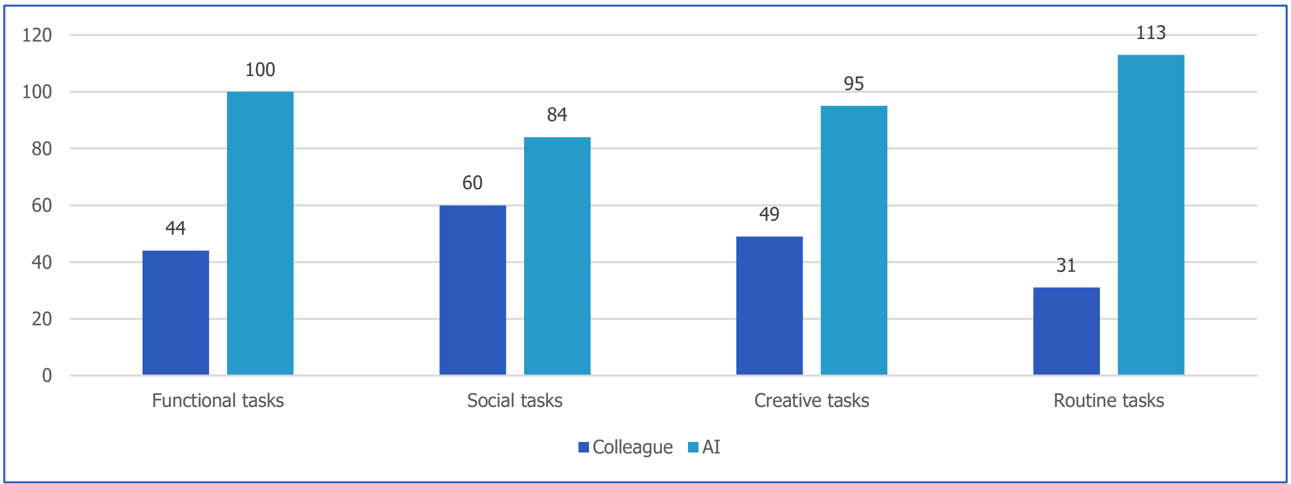

Figure 1. The structure of requests to AI and colleagues by task type at Company A.

At Company B, the consultation structure is mixed. Functional and social requests are more often resolved through interaction with colleagues, whereas when performing routine and creative tasks, employees rely more often on AI (Figure 2). This behavioural pattern may indicate an intermediate stage of digital transformation, or a balance between socio-technical systems, where human interaction continues to play a leading role.

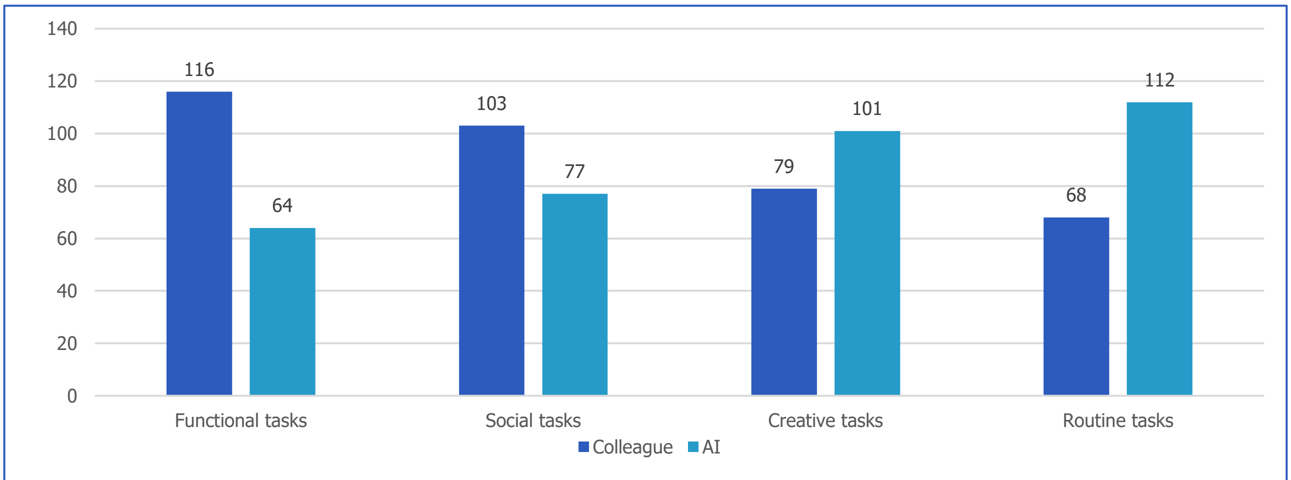

Figure 2. The structure of requests to AI and colleagues by task type at Company B.

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At Company C, the distribution of requests is more balanced. The frequency of turning to colleagues and AI for social and creative tasks is almost the same. At the same time, when it comes to functional tasks, turning to colleagues is more common, whilst for routine work, there is a clear preference for turning to artificial intelligence (Figure 3). This distribution indicates a combination of traditional communication practices with a gradual expansion of the role of algorithmic systems, which corresponds to the stage of moderate digital maturity.

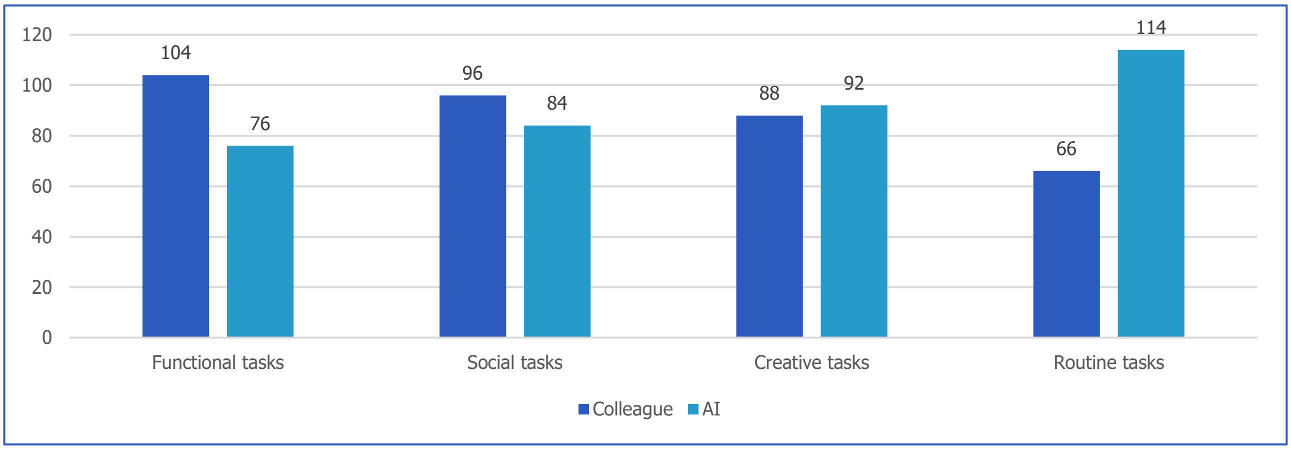

Figure 3. The structure of requests to AI and colleagues by task type at Company C.

Analysis of the results shows that all three companies actively use AI tools to perform creative and routine tasks. This indicates growing confidence in AI technologies capable of generating new ideas and optimizing standard processes. At the same time, social and functional tasks remain areas of key importance where interpersonal interaction, colleagues' experience, and contextual knowledge are essential. The exception is Company A, which has already transitioned to a model of intensive algorithmic communication.

Thus, the differences observed between the companies reflect varying levels of digital maturity and the degree to which AI has been institutionalized in everyday practices. This directly influences the structure of the communication network, the balance between human and algorithmic agents, as well as the distribution of interaction hubs within the knowledge management system.

Analysis of the respondents' motivations for turning to artificial intelligence

Within the scope of the study, particular attention was paid to analyzing the motivations for turning to artificial intelligence and colleagues as sources of assistance. To systematize the findings, the following motives were identified: speed of obtaining results, experience, reliability, and accessibility. It was precisely the comparison of these motives that allowed us to understand the logic behind the choice of the appropriate source for support in performing different types of tasks.

Consequently, the relative importance of individual motives was established for each category of tasks, specifically functional, social, creative, and routine tasks. The results obtained made it possible to assess in which situations artificial intelligence is more appropriate, and which situations favour traditional professional interaction with colleagues.

The results of the analysis of respondents' motives for turning to AI at Company A showed that when performing routine tasks, the key motives for using AI are speed and experience. This can be explained by the repetitive nature of such tasks and the possibility of quickly obtaining ready-made solutions (Figure 4).

When it comes to creative tasks, the factors of experience and speed are of the greatest importance, outweighing other considerations. These findings may be linked to the fact that AI is perceived as a tool to support the creative process. Using it not only helps to generate ideas quickly, but also broadens the range of possible solutions and reduces the workload on the user.

It has also been established that when performing social tasks, the most significant motives for using AI are the speed of response and the system experience. The significance of these factors may be linked to the need for rapid and expert support in everyday social contexts.

For functional tasks, the most significant motives for using artificial intelligence are the speed and accessibility of the system. The importance of these factors is driven by the need for prompt access to information and the ability to use technology continuously within the workflow.

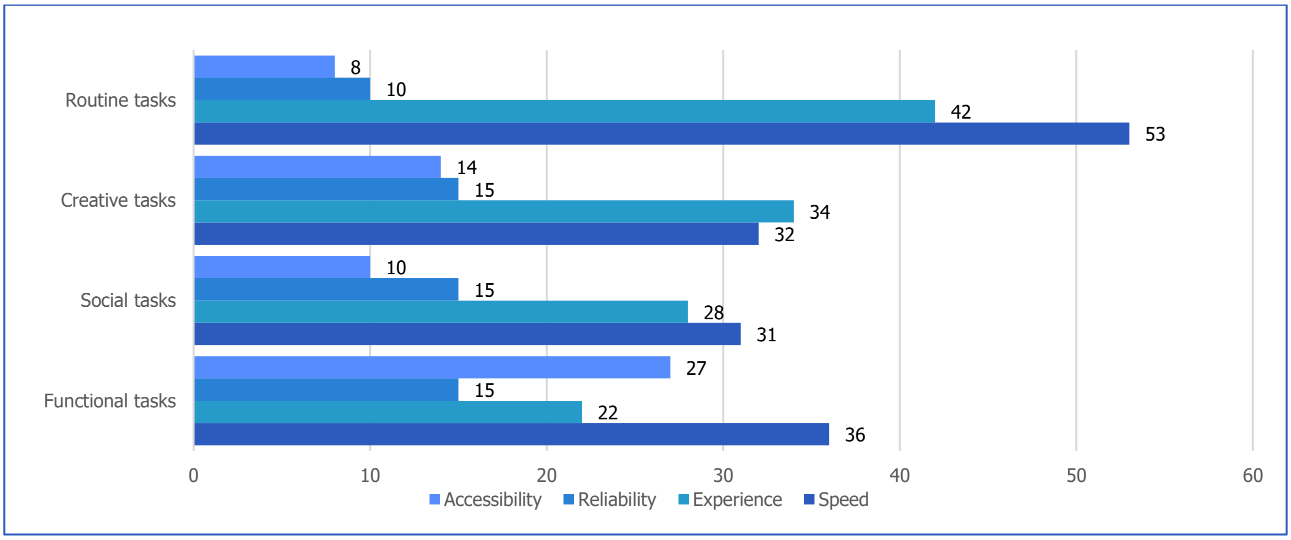

Figure 4. Distribution of motives for selecting AI to solve different types of tasks at Company A.

An analysis of motives at Company B revealed that, when performing routine tasks, the most significant reason for using artificial intelligence is the speed of obtaining results, whilst the second most significant reason is the system experience (Figure 5). This result may be linked to employees' desire to reduce the time spent on repetitive tasks by using artificial intelligence technology. When performing creative tasks, the speed motive also dominates, whilst the system experience ranks second in importance. This result may indicate that artificial intelligence is perceived as a tool to support the creative process. Its use facilitates the rapid generation of ideas and helps to broaden the range of possible solutions. A similar trend is observed when performing social tasks. The most significant motive for using artificial intelligence is the speed of receiving a response, whilst the system experience is of secondary importance. These results may be linked to the need to quickly obtain recommendations or advice in situations requiring a rapid response. At the same time, a different pattern of motivations is observed when performing functional tasks. The most significant factor in the use of artificial intelligence is the system experience, whilst the speed of obtaining results comes second. This may be due to the more complex and professionally oriented nature of such tasks, for which the quality and validity of the information obtained are crucial.

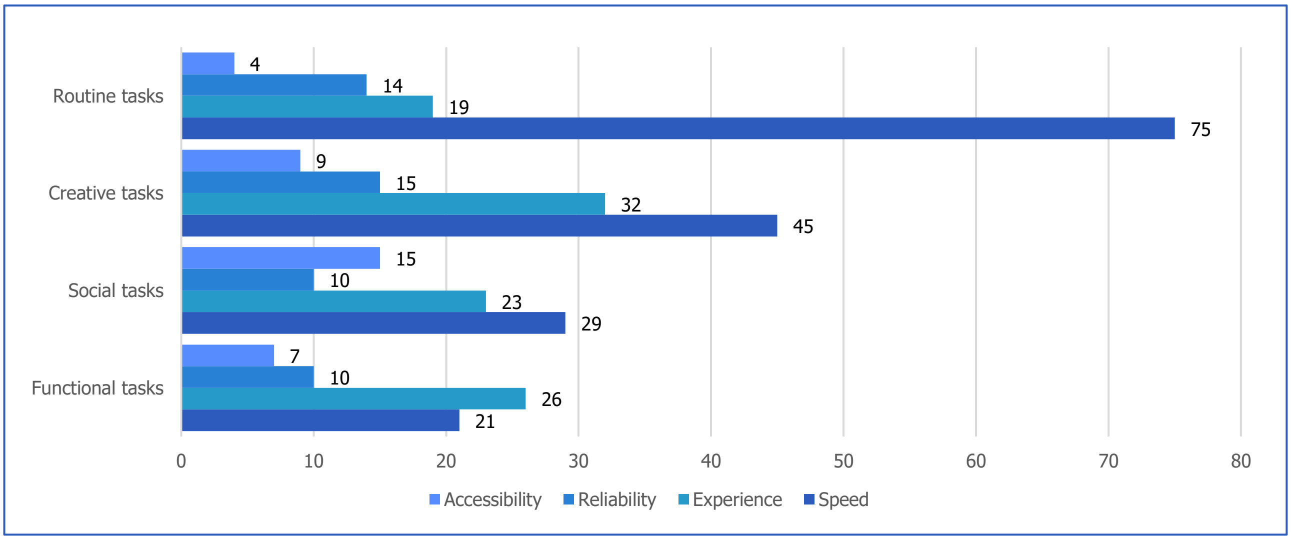

Figure 5. Distribution of motives for selecting AI to solve different types of tasks at Company B.

Analysis of the motives for using artificial intelligence in Company C showed that, when performing all types of tasks, employees value the speed of obtaining results most highly (Figure 6). The second most important motive is the accessibility of the system. This distribution of motives is observed when performing routine, creative, social, and functional tasks. The results obtained may indicate that employees perceive artificial intelligence as a fast and constantly available source of support in performing work tasks.

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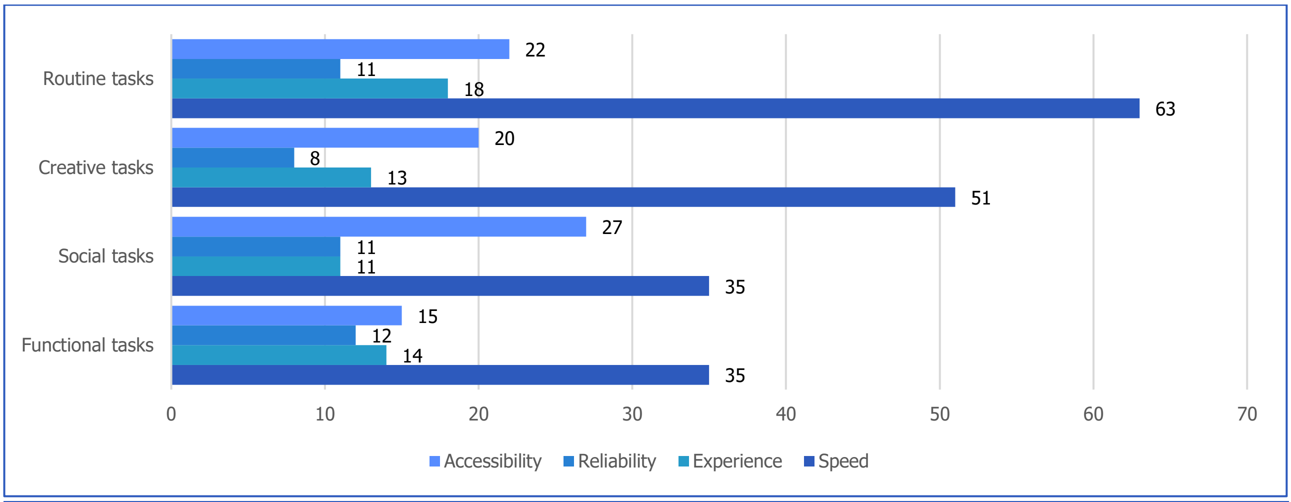

Figure 6. Distribution of motives for selecting AI to solve different types of tasks at Company C.

The summarized results of the analysis of the motives for using artificial intelligence indicate the presence of common trends in choosing AI as a source of support when performing various types of tasks. It has been established that, for routine, creative, and social tasks, the most significant motivations for using artificial intelligence are the speed at which results are obtained and the system experience. At the same time, for functional tasks, the decisive motivations are the speed and accessibility of the system. The results generally show that speed is a universal motive for using AI, regardless of the type of task. At the same time, the second motive varies depending on the nature of the activity. For routine, creative, and social tasks, the system experience takes on greater importance, whereas for functional tasks, accessibility is of greater importance. This confirms that choosing artificial intelligence as a source of support is determined not only by the general advantages of the technology, but also by the specifics of a particular type of task.

Analysis of the reasons respondents turn to colleagues.

The next stage of the analysis involved examining the reasons why respondents turned to colleagues when performing different types of tasks. Examining these motives helps to identify the reasons for choosing human resources to solve professional tasks rather than using AI technology. An analysis of the distribution of factors such as speed, experience, reliability, and accessibility make it possible to identify situations in which interaction with colleagues is more appropriate and effective.

The results of the analysis of the motives for respondents turning to colleagues at Company A showed that, when performing routine tasks, the key motives for turning to colleagues are their experience and reliability (Figure 7). This distribution of motives reflects the team's focus on achieving stable results and their trust in their colleagues' professional competence.

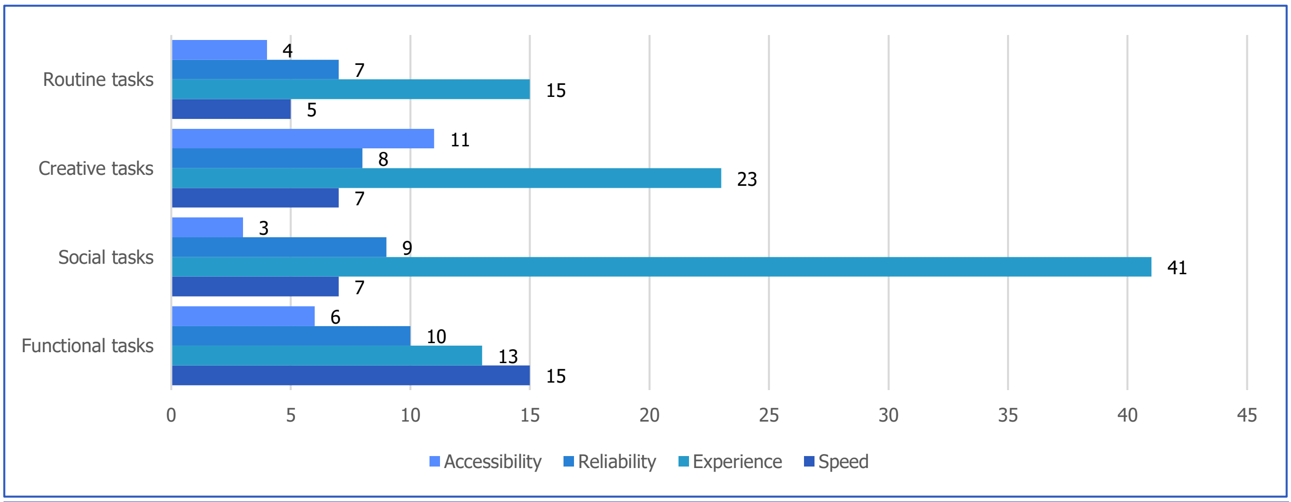

Figure 7. Distribution of motives for choosing a colleague to solve different types of tasks at Company A.

It has also been established that, when performing social tasks, the primary motive for turning to colleagues is experience, whilst accessibility is the second most significant factor. The results obtained reflect the team's focus on competence and the stability of human interaction when solving social tasks.

When performing creative tasks, the motives of colleagues' experience and reliability are of the greatest importance. Such a trend indicates the focus of staff on stable collective interaction and the use of practical experience in the process of seeking new solutions.

It was also shown that, for performing functional tasks, the leading motives for turning to colleagues are speed and experience. The significance of these factors may be due to the need for rapid access to applied professional knowledge and an understanding of the context.

An analysis of the motives for turning to colleagues at Company B revealed certain differences depending on the type of task. For example, when performing routine tasks, the leading motive for turning to colleagues is reliability, whilst experience is the second most significant (Figure 8). This result may be linked to the desire of the team to obtain predictable and stable outcomes and to draw on the practical experience of colleagues when carrying out standard work procedures.

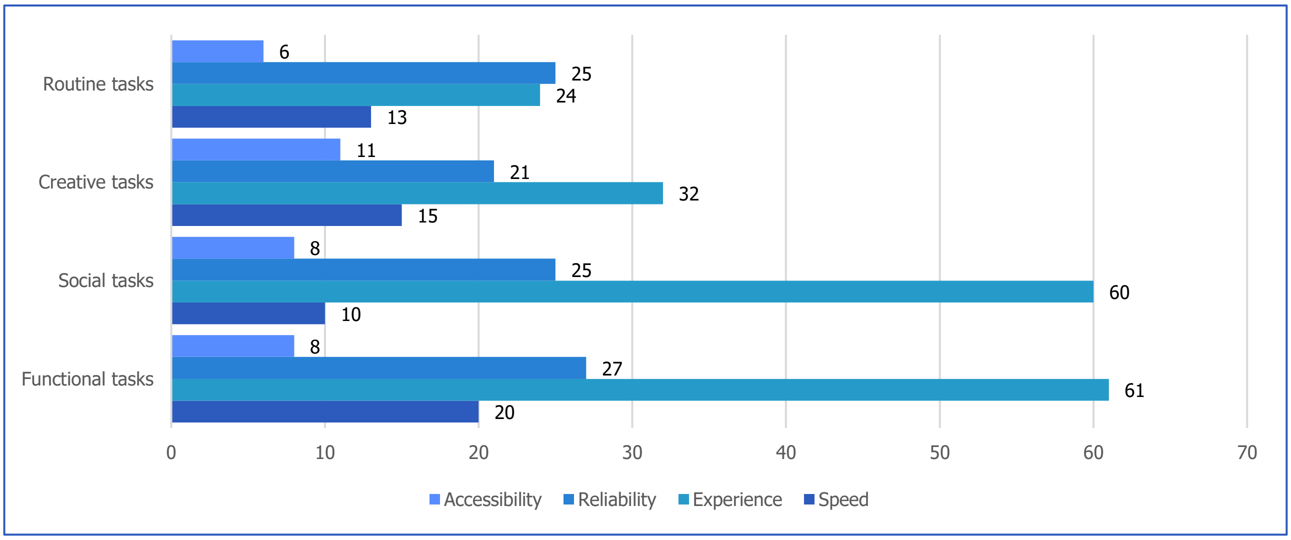

Figure 8. Distribution of motives for choosing a colleague to solve different types of tasks at Company B.

When performing creative tasks, the experience of colleagues is the most important factor, whilst reliability ranks second in terms of importance. The results obtained may indicate that employees are focused on using their colleagues' professional experience when seeking new ideas and solutions.

A similar distribution of motives is observed when it comes to social tasks. It was found that experience is also the leading motive for turning to colleagues, whilst reliability is of secondary importance. This result may reflect the importance of professional competence and a practical understanding of the situation in the process of interpersonal interaction.

A similar trend is observed when it comes to performing functional tasks. The most significant motive for approaching colleagues is experience, whilst reliability ranks second. This may be due to the need to obtain professionally grounded recommendations and to use specialized knowledge when performing functional tasks.

The results of the analysis of the reasons why respondents turn to colleagues at Company C showed a consistent distribution of reasons across all types of tasks. When performing routine, creative, social, and functional tasks, experience is the most significant reason for turning to colleagues, whilst reliability is the second most significant (Figure 9). This distribution of motives may indicate that employees primarily focus on their colleagues' practical professional experience when solving work tasks. At the same time, the reliability of interpersonal interaction plays an important role, ensuring trust in the recommendations received and contributing to the stability of the results of collaborative work.

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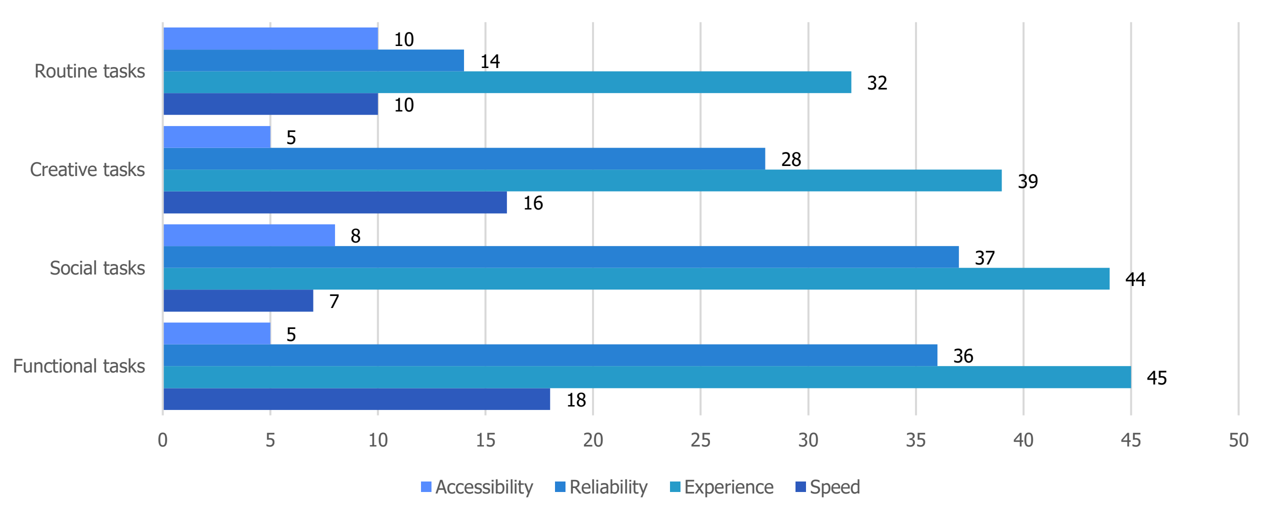

Figure 9. Distribution of motives for choosing a colleague to solve different types of tasks at Company C. *(Source: Created in Microsoft Excel)*

An overview analysis shows that in all three companies, respondents primarily rely on the experience and expertise of their colleagues in work processes. Reliability also plays an important role, particularly in Companies B and C. On the other hand, the motives of speed and accessibility are of secondary importance. The exception is Company A, where speed becomes one of the key factors in turning to colleagues when performing functional tasks. Overall, the results confirm that, within the system of communication relationships, colleagues' professional competence and reliability are the main criteria for choosing them.

DISCUSSION

The study of the role of artificial intelligence in shaping human-algorithm interaction within product IT organizations provides new insights into the impact of digital agents on the transformation of communication networks. The study documents both structural changes in social networks and shifts in the behavioural patterns of interaction participants. The findings are consistent with the research by Meng et al. (2025) on the impact of human-AI collaboration on the organizational environment. The authors show that the integration of AI can alter the nature of interpersonal communication and social interaction among employees in the workplace.

It was also found that, in all the organizations under study, the AI node accumulates the largest proportion of employees' information requests. AI functions as a key communication hub through which the majority of information flows pass. This position within the network confirms that the integration of AI shifts the balance of communication towards the technological hub, transforming it into a vital element of organizational interaction. These observations are consistent with the study by Dell'Acqua et al. (2025), which shows that artificial intelligence is no longer limited to the role of a passive tool but functions as a full participant in collaborative work. As a result, AI is capable of assuming roles previously associated primarily with human participants.

At the same time, the study's findings suggest that this functional role of AI may reduce the need for direct contact between employees, leading to a decrease in the density of communication networks. These observations are consistent with the study by Meng et al. (2025), which shows that collaboration between humans and AI can reduce the frequency of interpersonal communication within organizations.

The findings also point to a weakening of the traditional "human–technology" dualism. In the companies studied, the digital agent appears not as an external tool, but as a component of organizational practice, consistent with the sociomaterial approach to understanding the interrelationship between technology, labour, and organization (Orlikowski & Scott, 2008).

The analysis also shows that AI plays an active role not only in the distribution of information flows but also in the performance of specific work tasks. An analysis of employee behaviour patterns revealed the emergence of a hybrid model of task distribution between human and algorithmic participants (Leonardi, 2011; Faraj et al., 2018). It was also found that employees choose a source of support (human/AI) depending on the nature and complexity of the task. This indicates the use of selective strategies when choosing a source of support. These findings are consistent with research on human-AI interaction in organizations, which shows that AI integration facilitates a hybrid division of tasks and the formation of new models of interaction between humans and algorithmic systems (Jarrahi, 2018; Raisch & Krakowski, 2021; Kellogg et al., 2020).

Overall, the findings allow us to conclude that a new form of hybrid collaboration is emerging in the organizations studied, which is consistent with the research by Bankins et al. (2024). The authors demonstrate that the integration of AI into the organizational environment facilitates the formation of new models of interaction at the individual, group, and organizational levels. Thus, the AI node gives rise to human-algorithm connections as a distinct type of communicative relationship. These connections determine the specific functioning of the hybrid network and distinguish it from the traditional social environment. These findings are also consistent with the research by Pachidi et al. (2018), which shows that the integration of AI transforms the organizational environment, employees' expertise, professional boundaries, and coordination models.

However, it is worth noting that the study’s findings are limited by the specific nature of the sample, which consists solely of IT organizations. For more generalized conclusions, the study should be extended to other sectors and countries, which will provide a broader perspective on the role of AI in shaping human-algorithm interaction across different organizational contexts.

CONCLUSIONS

The study empirically demonstrates that the integration of artificial intelligence influences the structure of social interaction and the distribution of roles within an organization. The findings also describe in detail the mechanisms through which digital agents influence the organizational environment. The study showed that, due to high centrality and closeness measures, AI not only integrates into the communication network but also occupies a leading position within it. It was established that AI concentrates information flows and occupies a central position in the network, but does not perform the functions of an active intermediary in the classical network sense.

The absence of autonomous initiation of communication and outgoing ties deprives AI of the ability to act as a “bridge” capable of uniting weakly connected or isolated parts of the organizational network. Taking this into account, its influence on the topology of interactions is realized not through the direct “linking” of participants, but through the reorganization of human mediation around it. The study also demonstrated that information received from AI is incorporated into subsequent exchanges via human intermediary nodes. Thus, the results show that digital agents are becoming an important structural element of organizational communication networks.

An important direction for further research is to explore ways to reduce dependence on a single digital agent by introducing more flexible interaction mechanisms and creating additional channels for knowledge exchange.

ADDITIONAL INFORMATION

AUTHOR CONTRIBUTIONS

All authors have contributed equally.

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CONFLICT OF INTEREST

The Authors declare that there is no conflict of interest.

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ДОСЛІДЖЕННЯ РОЛІ ШТУЧНОГО ІНТЕЛЕКТУ У ФОРМУВАНІ ЛЮДИНО-АЛГОРИТМІЧНИХ ВЗАЄМОДІЙ

Дослідження присвячене ролі штучного інтелекту у формуванні людино-алгоритмічної взаємодії (ЛАВ) та визначенню його структурної позиції в комунікаційних мережах. Теоретико-методологічною основою дослідження є методологія аналізу соціальних мереж (SNA) та положення акторно-мережевої теорії (ANT). Емпіричну базу сформовано на основі опитування 145 фахівців трьох IT-компаній.

У результаті дослідження виявлено структурні зміни комунікаційних мереж і трансформацію моделей взаємодії учасників. Установлено низький рівень щільності досліджуваних мереж. Отримані результати пояснюються інтеграцією штучного інтелекту в комунікаційну мережу організації, що супроводжується скороченням міжособистісних зв'язків і зниженням загальної щільності мережі. Також установлено, що штучний інтелект має найвищі значення вхідної центральності в усіх організаціях і характеризується максимальною доступністю, що свідчить про його структурну впливовість у комунікаційних процесах. Водночас нульові значення показника серединності свідчать про те, що штучний інтелект не виконує функцій посередника в передачі інформації та не ініціює комунікації. Установлено, що інформація, отримана від штучного інтелекту, поширюється через посередників у межах окремих груп. У ході дослідження не підтверджено впливу штучного інтелекту на показник геодезичної дистанції мереж.

Аналіз моделей поведінки та мотивів звернення до штучного інтелекту як джерела допомоги виявив формування гібридної моделі розподілу завдань. Штучний інтелект переважно залучали до виконання креативних і рутинних операцій, водночас соціальні завдання вирішували через міжособистісну взаємодію. Винятком є одна компанія, яка демонструє ширше залучення штучного інтелекту навіть у соціальному контексті. Установлено селективний характер вибору джерел підтримки залежно від типу завдань і домінування мотивів швидкості та досвіду при зверненні до штучного інтелекту, а також досвіду й надійності при зверненні до колег.

Результати свідчать про еволюційний характер формування людино-алгоритмічної взаємодії та демонструють, що інтеграція штучного інтелекту змінює не лише технічні процеси, а й соціальну логіку комунікацій. Виявлені відмінності між компаніями інтерпретуються як різні рівні цифрової зрілості та підтверджують активну роль штучного інтелекту у формуванні гібридних соціотехнічних систем.

Ключові слова: бізнес-адміністрування, менеджмент, цифрова трансформація, штучний інтелект, взаємодія людини з алгоритмом, соціальні мережі, комунікація, управління людьми

JEL Класифікація: M0, M1