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**Identifying Face-to-Face Interaction Patterns
Related to Depressive Symptoms in Organizations
through Integrated Observation with Wearable Devices**



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Abstract

Sociometric wearable devices are sensors designed to automatically capture and collect human behavior including face-to-face interactions in real-world organizational settings. Sociometric wearable devices enable comprehensive observation of interactions within organizations, providing quantitative information about the potential influence that individuals can have on one another through their interactions. Depressive symptoms in organizations represent a significant issue as employees influence each other through their interactions. Depressive symptoms have been suggested to be influenced by the structural and physical interaction patterns of others with whom individuals interact. Specifically, the structure of interactions can influence depressive symptoms across multiple scales from the individual to the macro level, and physical movement within the interaction processes can be reduced and coordinated alongside one's own and others' depressive symptoms.

However, it remains unclear whether the influence of such interactions on depressive symptoms can be systematically identified through the comprehensive organizational face-to-face interaction data collected using wearable devices. This study aims to investigate structural and physical interaction patterns related to depressive symptoms within organization by using sociometric wearable devices. For this purpose, this study analyzed face-to-face interaction data measured using name-tag type sociometric wearable devices familiar to office workers. These devices captured face-to-face interactions through infrared communication with other devices while simultaneously recording body rhythm as physical movement patterns through accelerometers. The measurements were conducted in organizational units sharing the same workspace, comprising face-to-face interaction records of 449 employees across 10 organizations from various industries. The Center for Epidemiologic Studies Depression (CES-D) scale, a self-report depression scale developed for screening depression in the general population,

was used to measure depressive symptoms by quantifying both the variety and frequency of depressive symptoms of employees. The analysis was conducted using two approaches.

First, a social network analysis was conducted to comprehensively examine the interaction patterns between individuals and others. Face-to-face interactions among employees were monitored using wearable devices for more than 5 days in each organizational setting, encompassing weekly work patterns. These interactions were used to establish links between employees, with each link weighted by the interaction frequency of the corresponding pair, forming an organizational face-to-face interaction network. The structural characteristics of individuals in the organizational network were quantified at three different scales - individual, surrounding, and organizational - determined by the scope of interactions included in each analysis, and their associations with depressive symptoms were examined. The correlation analysis indicated that high density of face-to-face interactions at the surrounding level, reflecting the prevalence of interactions between an employee's interaction partners, was negatively associated with depressive symptoms. Particularly, the correlation between the interaction density at the surrounding level and depressive symptoms was more evident when employees frequently interacted face-to-face with partners who were also highly connected with each other. These findings suggest the importance of both densely connected structures at the surrounding level and the frequent direct interactions within such structures in relation to depressive symptoms.

Second, to examine how physical movements during interactions influence and relate to depressive symptoms between individuals, analyses were conducted on movement patterns of both individuals and their interaction partners, along with their depressive symptoms. Using wearable devices that detect subtle bodily rhythm before and during face-to-face interactions, physical engagement was defined as the increased frequency of bodily rhythm during face-to-face interactions to evaluate only the effects related to the

interactions. Results examining the correlations between physical engagement and depressive symptoms across an employee and their interaction partners revealed that physical engagement negatively correlated with depressive symptoms of the interaction partners. This correlation was significant even when interaction partners were limited to the two most frequently interacting individuals, demonstrating a robust characteristic among frequently interacting people. Furthermore, individuals who served as primary interaction partners for others, having substantial interactive influence within the organization, showed negative correlations across all combinations of physical engagement and depressive symptoms between themselves and their partners.

Wearable device observations of face-to-face interactions within organizations revealed that employees whose interaction partners were densely interconnected showed lower depressive symptoms, and employees whose interaction partners had lower depressive symptoms demonstrated higher physical engagement. Specifically, the interaction density and physical engagement, which showed a negative relationship with depressive symptoms among employees and their partners, were notably evident among frequently interacting partners, suggesting that these patterns of interaction density and physical engagement reflect qualitative characteristics of interactions with frequent partners and can be observed and influenced through direct face-to-face interactions. These findings emphasize the importance of considering the structural density among frequently interacting individuals, as well as the degree of physical engagement within their interactions, when analyzing depressive symptoms that can be influenced through interactions within an organization.

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1. Introduction

1.1. Wearable Devices for Measuring Face-to-Face Interactions within Organizations

Interactions within organizations entail the functional and social roles of organizational members. In particular, the importance of face-to-face interactions in organizational settings has been emphasized in various aspects. For example, face-to-face meetings facilitate a rapid understanding of each other's expertise, enabling effective role distribution and collaboration (Lewis, 2004). Teams engaging in face-to-face interactions tend to have more spontaneous communication, which helps reduce team conflicts (Hinds & Mortensen, 2005). Employees also prefer face-to-face interactions as a means of rich qualitative exchange such as energizing interactions and problem-solving (R. Cross & Gray, 2021). Furthermore, recent findings indicate that face-to-face emotional support correlates with lower depressive symptom severity, contrasting with social media-based support, which is associated with higher severity (Shensa et al., 2020). These examples illustrate how face-to-face interactions within organizations facilitate both functional and psychosocial exchanges between organizational members.

Sociometric wearable devices are sensors designed to capture and collect human behavior including face-to-face interactions in organizations (Olguin Olguin et al., 2009). These devices, commonly taking the familiar form of wearable name tags or badges in organizational settings, detect signals such as voice, location, and face-to-face situations, providing useful data for automatically collecting and monitoring patterns of face-to-face interactions as they occur in real organizational settings (Ito-Masui et al., 2021). By utilizing these devices, researchers have contributed to understanding the characteristics of face-to-face interactions within organizations. For example, one study demonstrated that observing workplace face-to-face interactions through wearable devices could capture

communication patterns between employees and departments that email data alone could not capture (Olguin Olguin et al., 2009). Other studies found that higher work productivity was associated with cohesive groups with close connections among employees (Wu et al., 2008; Watanabe et al., 2014). Additionally, in a study of students participating in a weekend remote camp house, sociometric wearable device was used to quantify the degree of social isolation in interactions, which was found to be associated to depressive symptoms (Elmer & Stadtfeld, 2020).

Sociometric wearable devices serve as an effective means of providing comprehensive and objective explanations of organizational interaction structures and potential influences that organizational members can exchange through face-to-face interactions. A distinctive feature of analyses through sociometric wearable devices is their capacity to collect data from entire groups rather than focusing solely on individual interaction data. While smartwatch or smartphone-based technologies primarily track individual behavioral patterns (Can et al., 2019), sociometric wearable devices capture group interaction patterns. Furthermore, face-to-face interaction data accumulated through observations in daily life using wearable devices has been reported to effectively explain the formation of cooperative relationships (Atzmueller et al., 2018), and the accessibility of organizational resources, such as information that supports task performance (Wu et al., 2008).

The present study is motivated to examine the relationship between individuals' depressive symptoms and influences from others on structure and physical movement of face-to-face interactions measured by wearable devices. The influences that employees exchange through workplace interactions, such as social support, constitute crucial resources for coping with stress and preventing depressive symptoms (Johnson & Hall, 1988; Tennant, 2001; Colligan & Higgins, 2006; Dollard et al., 2007). From this perspective, employees' depressive symptoms could be influenced not only by their own interactions but also by the interactions of other employees. In relation to these influences,

this study specifically focuses on two measurable factors through wearable devices: the structure of face-to-face interactions and physical movements during the interactions. This investigation builds on previous research indicating these factors can have influences with others' interaction patterns in relation to depressive symptoms. The following section will provide a detailed explanation of these research backgrounds.

1.2. Social Interactions in Organizations and Depressive Symptoms

One of the significant applications of comprehensive approach using sociometric wearable devices is employee mental health within workplace. Workplace is the primary organization where modern people spend most of their time and contribute to productivity of society. However, psychosocial factors in the workplace such as harassment, poor organizational climate, challenging relationships, and situations where employees face excessive work demands while lacking control over their tasks (Tennant, 2001; Colligan & Higgins, 2006; Dollard et al., 2007; Bonde, 2008) are closely associated with employee stress, which is recognized as a major cause of depression (Hansson et al., 2010; Read et al., 2015).

Interactions among employees are closely linked to individual psychosocial factors in the workplace. Studies using questionnaires have confirmed that interactions between employees are related to psychosocial factors in various ways. For instance, the degree of social support such as the closeness with colleagues and supervisors has been identified as a significant risk factor influencing mental health outcomes such as stress, absenteeism, and burnout across various occupations (Tennant, 2001). Studies show that work environments characterized by high job demands and with low control over workload present increased risks for job stress and depressive symptoms (Tennant, 2001; Dollard et al., 2007; Bonde, 2008) especially when combined with poor social support (Johnson & Hall, 1988; Dollard et al., 2007). Moreover, workplace interactions serve as a positive force by motivating employees and enhancing their work capabilities (Owens et al., 2016), as well as facilitating information sharing that positively affects workplace influence and performance (Brass, 1984; Sparrowe et al., 2001; Burt, 2004).

Some surveys include specific questions about contexts where direct interpersonal

interactions occur. For instance, in a study that identified poor social support as a significant risk factor for job stress, alongside situations of high job demands with low control, the questions directly addressed opportunities for workplace interaction, such as ‘could talk to co-workers during breaks’ and ‘could interaction with co-workers as part of their work’ (Johnson & Hall, 1988). Studies examining the energizing role of employee interactions have included assessments of interaction vitality and frequency, with questions such as ‘I feel increased vitality when I interact with this person’ and ‘I would go to this person when I need to be “pepped up”’ (Owens et al., 2016). Thus, such employee interaction patterns including interaction partners, frequency and the process are psychosocially significant factors for mental health. These considerations motivated this study to identify interaction patterns within organizations related to depressive symptoms through sociometric wearable devices. The following subsections will review prior research examining how an individual’s depression can be influenced through others’ interactions including structural and physical aspects of those interactions.

1.2.1. Structural Effects of Interactions on Depressive Symptoms

The structural aspects of interaction patterns are an important factor to consider when identifying social interactions related to depressive symptoms (Ueno, 2005; Cacioppo et al., 2009; Rosenquist et al., 2011; Santini et al., 2015; Schmälzle et al., 2017; Elmer & Stadtfeld, 2020; Reiner & Steinhoff, 2024). Social network analysis provides quantitative evaluation of network structural characteristics through various metrics, and these structural features have demonstrated their significance in relation to depressive symptoms in multiple ways.

Network size provides a quantitative approach to understanding the benefits of social relationships. Various studies have been conducted using surveys as a method of asking about the number of social relationships (Berkman & Syme, 1979; Burt, 1987; Reiner & Steinhoff, 2024; Santini et al., 2015; Ueno, 2005). Research has shown that social relationships serve as resources for mental health, as evidenced by their influence on mortality rates (Berkman & Syme, 1979) and reported levels of happiness (Burt, 1987). In relation to depressive symptoms, a substantial body of survey-based research has been conducted. Systematic reviews of these studies have consistently shown that individuals with larger and more diverse social networks encompassing family members, friends and colleagues demonstrate lower levels of depressive symptoms and reduced risk of depression onset (Santini et al., 2015). These protective effects have been significantly observed across different age groups, including adolescents and older adults (Ueno, 2005; Reiner & Steinhoff, 2024). In a study observing college students at a weekend camp using wearable devices, higher depressive symptoms were associated with less face-to-face interaction time (Elmer & Stadtfeld, 2020). Depressive symptoms have been associated with reduced social connections across studies.

Another significant structural characteristic of social network is density. In social network analysis, density is typically quantified as the proportion of actual relationships to the total number of possible social relationships among those surrounding individuals (Watts & Strogatz, 1998). In sociology, triadic relationships have been emphasized as crucial elements in the formation of new ties and strong relationships (Holland & Leinhardt, 1971; Granovetter, 1977; Onnela et al., 2007), and the density of social networks is associated with strongly tied group structures through the prevalence of these triadic relationships. Density provides information about social relationships beyond individual relationships. For instance, high-density rural social networks centered around kinship tend to facilitate social support and emotional bonds, while low-density urban social networks based on scheduled activities are characterized by rapid information sharing and adaptability to change (House, 1987). Since density requires information about social relationships not only of oneself but also of surrounding individuals, organizations and communities have primarily been the subjects of observation. Various studies have been conducted using sociometric wearable devices and surveys. In a study that observed face-to-face interaction networks of IT facility staff using sociometric wearable devices over approximately one month, results showed increased productivity with higher work speeds in dense and closed face-to-face interaction network structures (Wu et al., 2008). This suggested that such structures could facilitate effective knowledge sharing. Similarly, a study observing call center operators at two different centers for over a month using sociometric wearable devices found that the call center with higher face-to-face interaction network density handled more calls per hour (Watanabe et al., 2014). In a study of students at an entrance exam preparatory school, classes with higher face-to-face interaction network density during break times, as measured by sociometric wearable devices, showed higher average test scores (Watanabe et al., 2013). Another study focused on school classes found that lower density in relationship networks constructed through mutual nomination of

likability was associated with increased antisocial behavior (W. van den Bos et al., 2018).

Meanwhile, the relationship between network density and depressive symptoms remains understudied. A systematic review of studies involving community-dwelling elderly populations revealed that only 4 out of 127 studies examined network density through surveys and interviews, showing inconsistent findings (Reiner & Steinhoff, 2024). Similarly, research investigating the impact of early adolescent depressive symptoms on later online social network formation found that depressive symptoms did not significantly predict network density (Negriff, 2019). Despite this limited evidence in depression research, network density remains significant in understanding social support mechanisms, particularly in psychosocial stress responses. For instance, during social exclusion, which increases negative affect and decreases self-evaluation (Williams et al., 2000), and is known as a risk factor for depression (Rudert et al., 2021), adolescents with low online social network density show heightened activation of brain systems for social cognitive processing (Schmälzle et al., 2017), suggesting network density's role in how the brain manages stress responses in relation to social support.

Depressive symptoms are also associated with the macroscopic structure of social networks. The Framingham Heart Study, a cohort study that has followed community residents for over two decades, investigated social relationships through interviews and reported that depressive symptoms are correlated among people with close social relationships such as family members, neighbors, and friends (Rosenquist et al., 2011). This correlation extends up to three degrees of separation (friends of friends of friends), suggesting that depressive symptoms spreads through network structures in a manner similar to contagion. In a related analysis of the same cohort, researchers found that loneliness, a component of depressive symptoms, is associated with reduced social connections and tends to cluster at the periphery of entire social networks (Cacioppo et al., 2009). These contagion effects were stronger among close relationships such as mutual

friendships and next-door neighbors, and the authors suggest that the contagion can be induced through social interaction. In conclusion, these findings suggest that depressive symptoms, influenced by social relationships, can impact both the overall structure of social networks and the individuals within them.

In summary, empirical evidence has established the significance of social network structures in depressive symptoms across multiple scales, ranging from individual-level metrics such as the number of social ties to surrounding-level characteristics like network density, and extending to macroscopic network structures.

1.2.2. Characteristics of Physical Movement in Interactions Associated with Depressive Symptoms

Physical movement is a significant factor in assessing face-to-face interactions in relation to depressive symptoms (E. H. Bos et al., 2007; Joshi et al., 2013; Girard et al., 2014; Paz et al., 2022). In general, higher levels of depressive symptoms are associated with decreased physical movement. This relationship is observed to be bidirectional and has been well established through large-scale cohort studies using questionnaires to assess physical activity levels (Azevedo Da Silva et al., 2012; Pinto Pereira et al., 2014).

The relationship between depressive symptoms and physical movement is also observed in interaction. A study that interviewed patients with severe depressive symptoms and analyzed their nonverbal behavior through video recordings found that when the depressive symptoms improved, the amplitude and speed of head movements significantly increased (Girard et al., 2014). Similarly, a study that recorded and analyzed interview videos of depression patients and healthy controls observed that patients with severe depressive symptoms exhibited differences in upper body movements, particularly a significant decrease in head movement (Joshi et al., 2013).

Furthermore, physical movement during interactions can interact with the emotions and physical movements of the interaction partners. Video recording analysis studies have found that participants tend to unconsciously mimic their interaction partners' behaviors, such as foot shaking, face rubbing, and smiling. (Chartrand & Bargh, 1999). This mimicry behavior is supported by the mirror neuron system and plays a role in facilitating emotional connection by imitating the interaction partner (Paz et al., 2022). Studies using video analysis have found that the degree to which the timing and rhythm of physical movements are synchronized during an interaction is related to the smoothness of the interaction, liking for the partner (Chartrand & Bargh, 1999), and formation and inference of rapport

(Bernieri, 1988; Lakens & Stel, 2011).

Depressive symptoms are associated with impairments of physical and emotional coordination during interactions. Individuals with severe depressive symptoms have been reported to experience difficulties in engaging in social interactions and show reduced empathy, potentially triggering neural synchronization with their interaction partners leading to emotional contagion of the depressive state (Paz et al., 2022). Another research examining interviews with remitted depression patients has shown that when there is incongruence in nonverbal involvement behaviors (e.g. duration and frequency of gestures and head movements) between patients and interviewers, as evaluated through video recordings, they experienced higher incidence of stressful interpersonal events and increased risk of depression recurrence (E. H. Bos et al., 2007).

In summary, reduced physical movement and impaired behavioral coordination during face-to-face interactions are associated with depressive symptoms among interacting individuals. These effects are observed through expression, contagion, and impairment, and interact with both the emotional states and behaviors of their interaction partners.

1.3. Research Purpose and Approach

As introduced in Section 1.2, depressive symptoms are closely associated with structural and behavioral aspects of social interactions. While various studies utilizing surveys, video analysis, and sociometric wearable devices have suggested that individuals in interaction networks can be functionally and psychologically influenced by others' interactions and physical movements, it remains unclear how such influences can be identified in real organizational settings with regard to employees' depressive symptoms.

The purpose of this study was to investigate how interaction patterns captured by sociometric wearable devices relate to employees' depressive symptoms. For this purpose, analyses were conducted using face-to-face interaction data collected from organizational environments across various industries. Face-to-face interactions were measured using name tag-type wearable devices familiar to office workers (Ara et al., 2009; Wakisaka et al., 2009). These devices, equipped with infrared modules and accelerometers, captured face-to-face interactions through infrared communication with other devices while recording physical movement patterns. The measurements were conducted in organizational units sharing the same workspace, comprising face-to-face interaction records of 449 employees across 10 organizations. Depressive symptoms were measured using the Center for Epidemiologic Studies Depression (CES-D) scale (Radloff, 1977), which quantifies both the variety and frequency of depressive symptoms in the general population. The details of measurements are described in Sections 2.2.1, 2.2.2, 2.2.6, and 3.2.2.

The analysis was conducted using two approaches. First, social network analysis was employed to examine structural characteristics related to depressive symptoms within interaction structures at various scales (individual, surrounding, and organization-level), including interactions involving oneself and other employees. Second, the association

between physical movement patterns during interactions and the depressive symptoms of employees involved in those interactions and their interaction partners was investigated.

1.4. Structure of Thesis

As shown in Fig. 1.1, this thesis consists of five chapters. Chapter 1 explained the motivation and purpose of investigating the relationship between organizational interaction patterns measured using sociometric wearable devices and depressive symptoms. Chapter 2 designs social network analysis methods to examine the structural characteristics of interactions measured through wearable devices and investigates how network structures at different scales relate to depressive symptoms. Chapter 3 utilizes interaction and physical movement data collected through wearable devices to identify physical movement patterns during interactions and examines their relationship with depressive symptoms of individuals and their surrounding colleagues. Chapter 4 presents a general discussion synthesizing the findings from Chapters 2 and 3. Chapter 5 summarizes the research conclusions and discusses future prospects based on the findings obtained in this research.

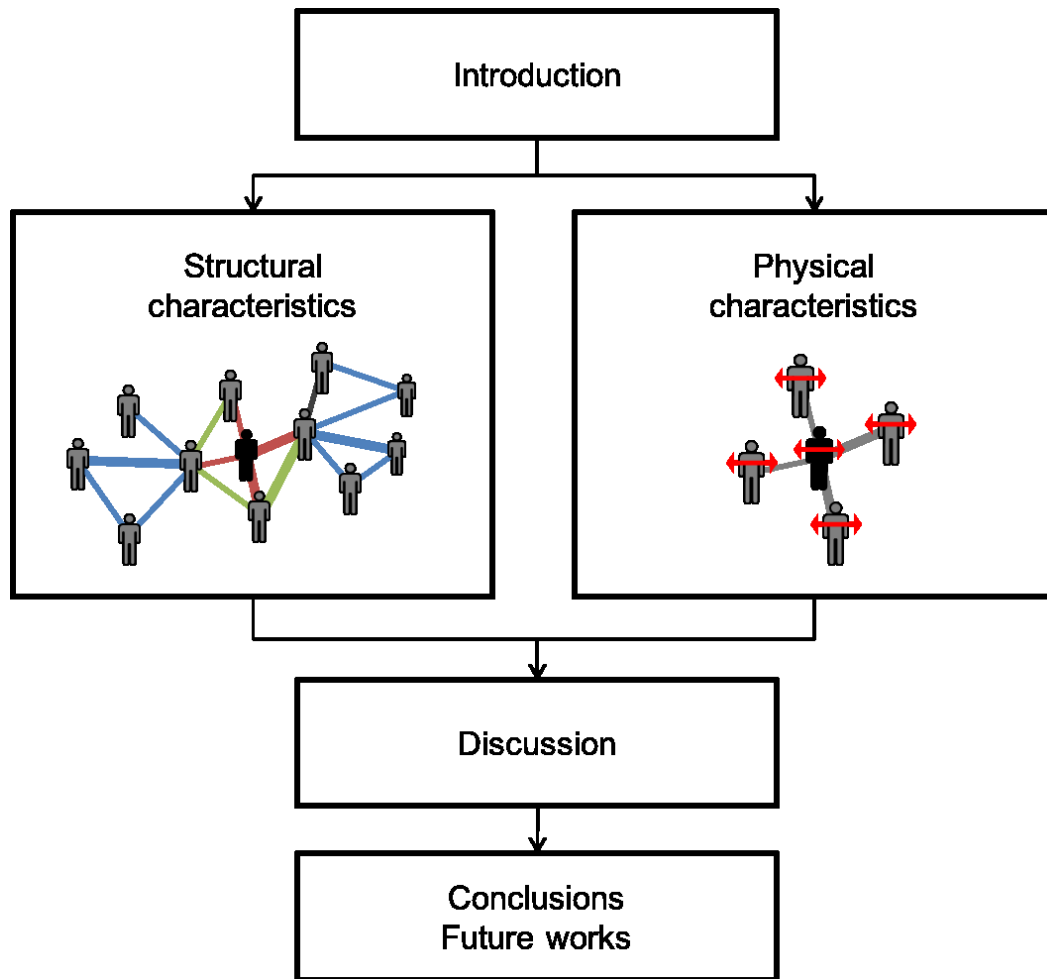


Figure 1.1 Structure of thesis. Chapter 1 consists of introduction, Chapter 2 analyzes structural characteristics of face-to-face interaction network, Chapter 3 analyzes physical characteristics during face-to-face interactions, Chapter 4 contains comprehensive discussion, and Chapter 5 presents conclusions and future works.

2. Structural Analysis of Face-to-Face Interaction Networks using Wearable Device and Depressive Symptoms

2.1. Aim

As introduced in Section 1.2.1, depressive symptoms have been implicated in social interactions across individual, surrounding, and macro-network scales. This study investigated the association between structural characteristics of face-to-face interaction networks within organizations measured by sociometric wearable devices, and depressive symptoms. This study constructed social networks based on interaction frequencies captured by wearable devices and quantified structural characteristics for each employee at individual, surrounding, and organizational levels using social network analysis metrics. The analysis was conducted across 10 organizations from various industries, with results examined both at the entire dataset and within individual organizations to verify the consistency of findings across different organizational settings.

2.2. Methods

2.2.1. Participants

This study used a dataset collected by the World Signal Center, Hitachi, Ltd. in 2009 from ten organizations in Japan. The dataset includes various organizations such as financial systems, public systems, call centers, IT services, personnel applications, industrial equipment, medical equipment, and insurance, making it suitable for examining general characteristics across different organizational types. The observation period was more than five days for all organizations (mean = 11.5 days, SD = 7.2), capturing at least a week of work patterns. The dataset initially included 470 employees, but 449 employees were analyzed after eliminating unreliable data due to insufficient records. Detailed data preprocessing procedures are described in Section 2.2.3. An overview of the organizational dataset is presented in Table 2.1.

During the measurement period, participants wore wearable devices upon arrival at work and performed their usual work activities. All employees in the target organizations were informed about the purpose of the measurement and the use of the data. The measurement was conducted only with participants who provided informed consent. The dataset was collected under Hitachi's ethical and personal information protection guidelines and was provided for academic research purposes under strict privacy protocols. All organizations and employees in the dataset were fully anonymized to prevent the identification of specific individuals or organizations.

Table 2.1 Overview of Dataset. Each row represents 10 organizations observed through wearable devices, while columns show their occupation category, number of participants, and data collection period. The numbers for participants and collection period indicate those used in the analysis after excluding participants and observation days with insufficient wearable usage records. Numbers in parentheses show total observations before preprocessing. The preprocessing procedure is detailed in Section 2.2.3. All workplaces and employees have been anonymized.

Occupational category	Number of participants	Collection period - days
Financial system	90 (93)	5 (6)
Public system	44 (55)	29 (29)
Call center	51 (52)	11 (15)
IT service	32 (33)	15 (24)
Personnel application	34 (34)	15 (24)
Industrial equipment	31 (33)	11 (15)
Medical equipment	56 (58)	9 (12)
Industrial equipment	18 (19)	5 (5)
Insurance	25 (25)	23 (54)
Industrial equipment	68 (68)	12 (19)

2.2.2. Measurement of Face-to-Face Interaction

Face-to-face interactions among employees were measured using a name-tag type wearable device (Fig. 2.1a; Business microscope, Hitachi, Ltd., Japan) specifically designed for workplace environments (Ara et al., 2009; Wakisaka et al., 2009). This wearable system has contributed to comprehensive and objective measurements of face-to-face interactions within organization across various studies. The device is compact in size ($73 \times 98 \times 9$ mm) and lightweight (62g), ensuring comfortable wear during regular work activities (Wakisaka et al., 2009). The familiar name-tag format and lightweight design allow employees to carry out their usual work activities without being physically conscious of wearing it. Additionally, the device features optimized power consumption and memory usage, allowing for approximately 24 hours of operation without charging, which further enhances its practicality in workplace settings.

The device is equipped with multiple infrared modules which can detect other devices within a 2-meter range at 120 degrees horizontally and 60 degrees vertically (Fig. 2.1b). This system is designed to detect typical face-to-face interactions in workplace settings, and has been verified to accurately capture various interaction scenarios such as temporary standing meeting, sitting meetings, and interactions between standing and seated individuals, as shown in Fig. 2.1b (Wakisaka et al., 2009). When interactions occur, the devices exchange their owners' IDs, allowing for the recording of face-to-face interactions at one-minute intervals.

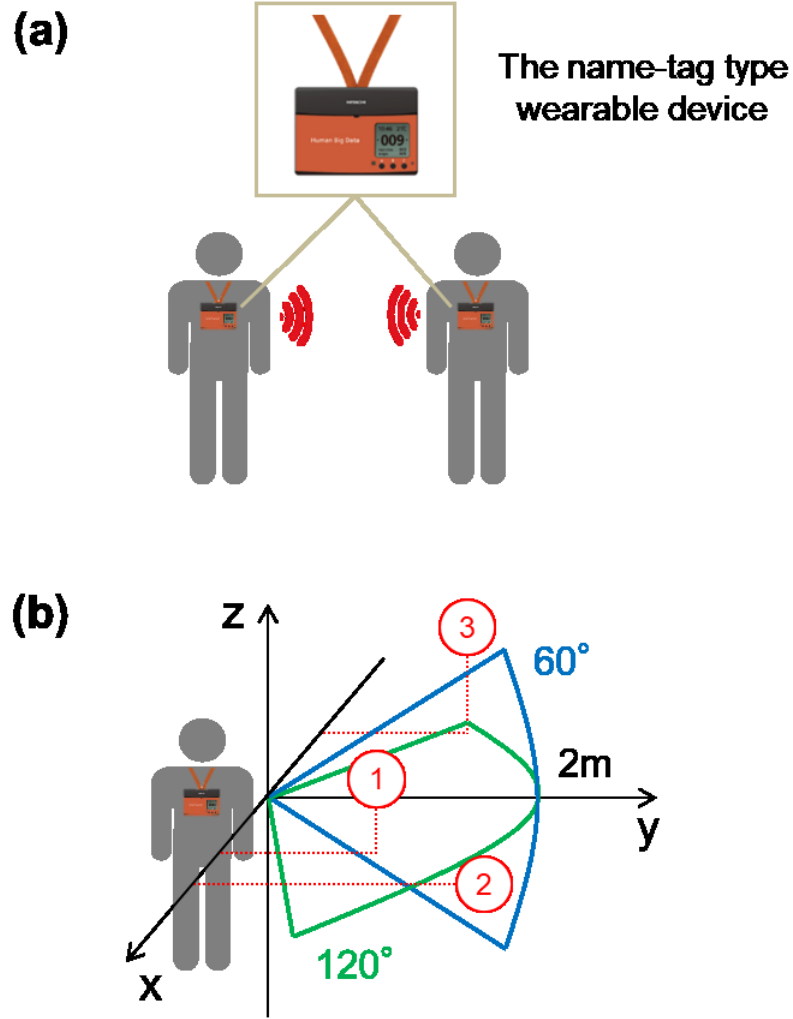


Figure 2.1 Detection of face-to-face interaction. a) The infrared module of a name-tag type wearable device communicates with other wearable devices' infrared modules to record face-to-face interactions. b) Detection range of the infrared module and previously verified interaction positions (marked as 1, 2, 3 in red circles) from previous research (Wakisaka et al., 2009). The verified positions from previous research in x, y, z axis order (in cm) were: Position 1 (30, 100, 40) representing a temporary standing meeting, Position 2 (50, 150, 0) representing a sitting meeting, and Position 3 (-50, 100, 50) representing a meeting where one person is seated and another is standing.

2.2.3. Preprocessing

In the detection of face-to-face interactions using name-tag-type wearable devices, misalignments can occur due to body orientation, posture, or movement, potentially causing missed detections. These misalignments between infrared sensors result in short empty intervals between recorded interaction events. While these intervals can represent either sensor misalignments or actual intermittent interactions, treating interactions occurring within short intervals as continuous interactions was determined to be more reasonable than considering them as completely new contextual encounters. Data preprocessing was implemented where face-to-face interactions occurring within intervals of less than five minutes were considered as continuous interactions. This correction helps prevent overestimation of interaction frequencies between employees, making it suitable for evaluating more long-term interaction patterns. Appendix A further validates that this correction criterion does not substantially affect the main findings.

To ensure data reliability, criteria were established for participant inclusion. Employees with less than five hours of device usage or less than one hour of total face-to-face interaction time were excluded from the analysis. After applying these criteria, the final sample consisted of 449 employees, with 21 employees being excluded due to insufficient data. Details of the datasets before and after preprocessing can be found in Table 2.1, where numbers in parentheses represent values prior to preprocessing.

2.2.4. Face-to-Face Interaction Network

As shown in Fig. 2.2, face-to-face interaction networks were constructed from observed interactions between employees. First, the frequency of interactions between each pair of individuals was calculated. These interaction frequencies were normalized by the total number of days during which wearable devices were operational within each organization. This normalization procedure, which produces a measure of daily interaction frequency, enables meaningful comparisons across organizations with different observation periods.

The normalized interaction data was then used to construct a weighted network representation of face-to-face interactions within each organization. In this network, nodes represent individuals, while edges represent observed face-to-face interactions between pairs of individuals. The weight of each edge corresponds to the normalized frequency of interactions between the connected pair. The complete face-to-face interaction network for each organization was assembled by combining all observed interactions and their corresponding weights. The weighted edges provide a quantitative measure of interaction intensity, reflecting the average daily frequency of face-to-face encounters between organizational members.

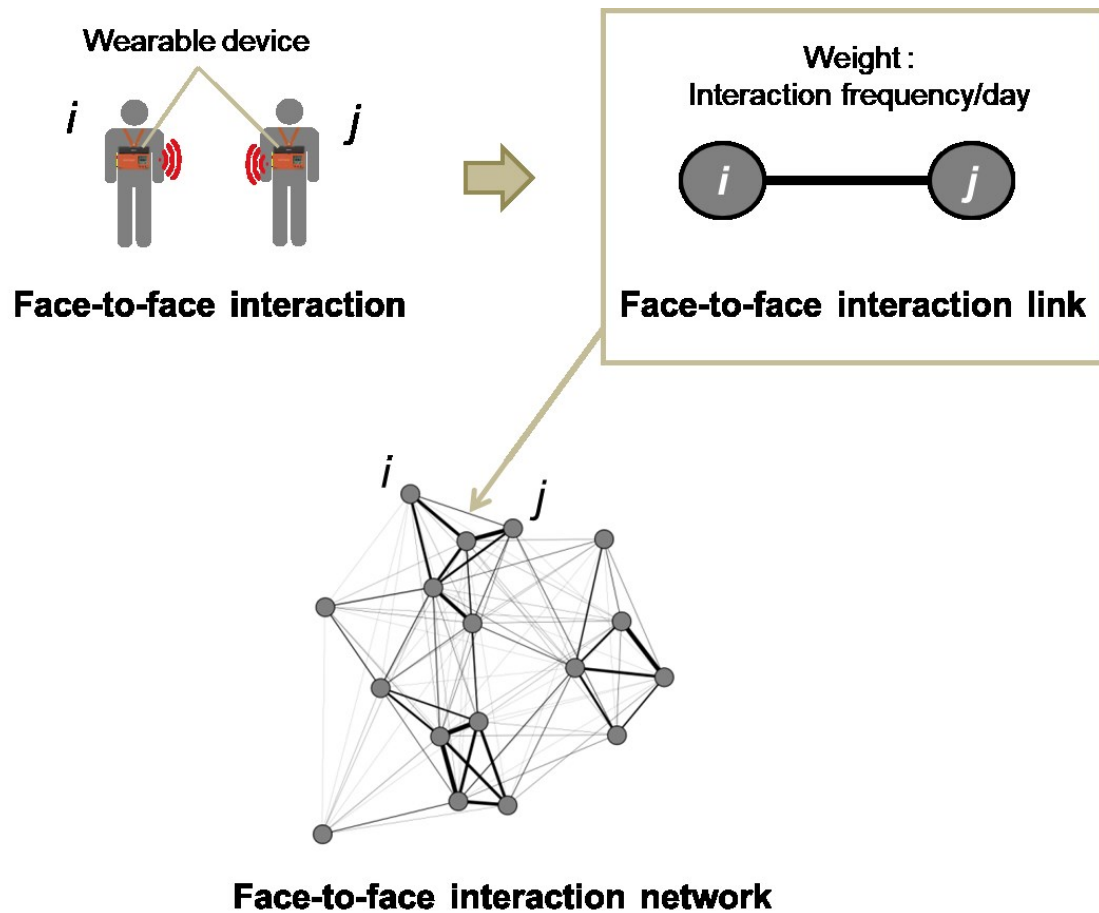


Figure 2.2 Process of constructing face-to-face interaction network from face-to-face interactions between two employees (i, j). Face-to-face interaction records observed through wearable devices between employees i and j are represented as a link weighted by the daily average number of interactions. The organization's integrated face-to-face interaction network is constructed by performing the same process for interactions between all employees.

2.2.5. Social Network Characteristics

The analysis of social networks spans multiple scales of interaction patterns. This study examines 11 distinct network metrics across three levels: individual, surrounding, and organizational. An overview of metrics at each scale is shown in Fig. 2.3.

Individual level

At the individual level, network metrics characterize an individual's interaction patterns. *Degree* represents counts the total number of unique connections. The equation is given as:

$$Degree_i = k_i \quad (1)$$

Here, k_i represents indicates the number of interaction partners that i has. This shows how many people i had face-to-face interactions with.

Weight represents how frequently interactions occur. The equation is given as:

$$Weight_i = \sum_j w_{ij} \quad (2)$$

Here, w_{ij} represents the interaction frequency between i and j (total number of interactions divided by the number of days of measurement), and the sum of these values represents daily interaction frequency of i .

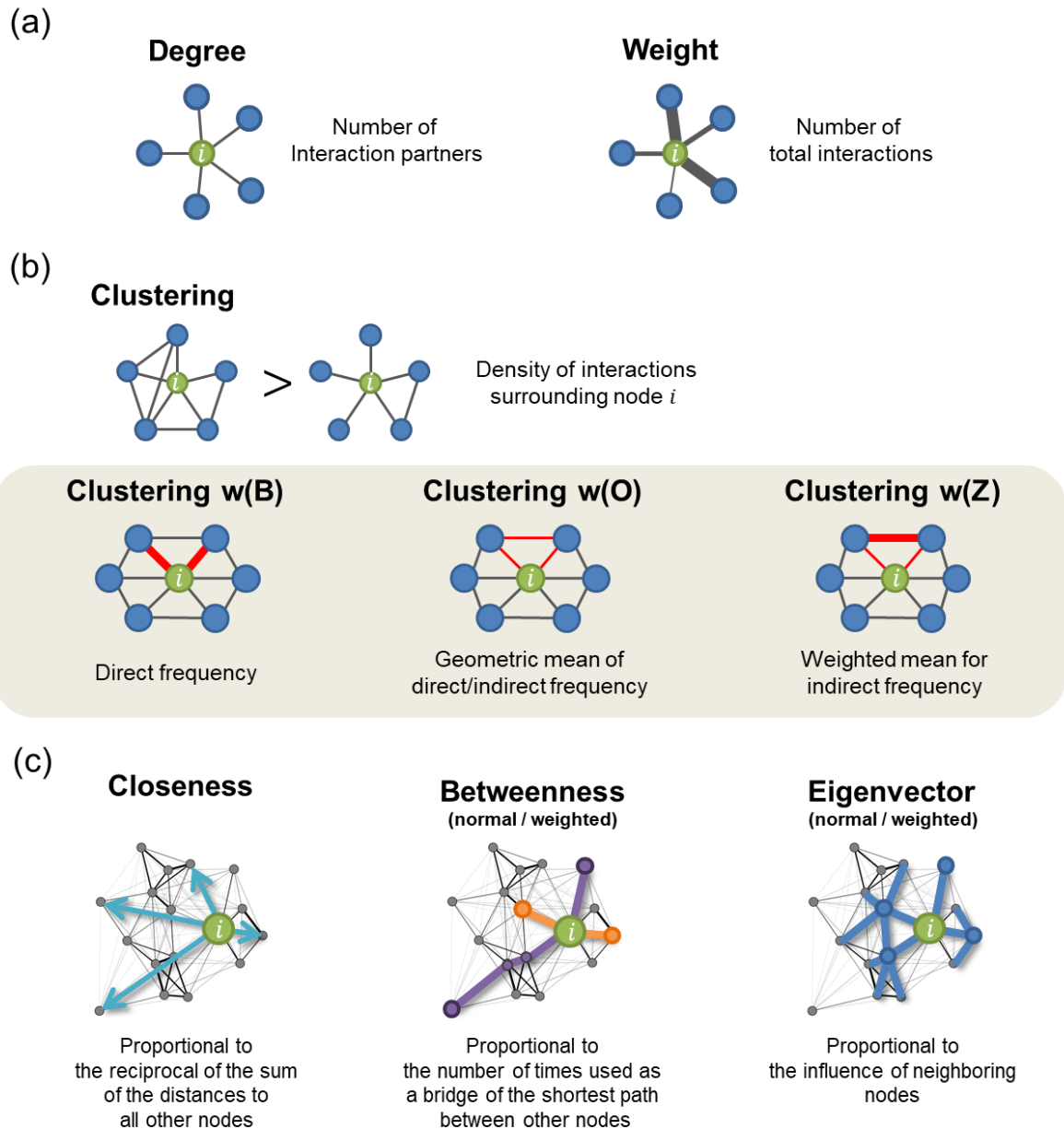


Figure 2.3 Overview of social network characteristics for node i . a) Individual scale: *Degree*, *Weight*. b) Surrounding scale: *Clustering* and weighted versions of *Clustering*. In the weighted version of clustering, the red lines indicate the frequency of interactions that are relatively emphasized. c) Organizational scale: *Closeness*, *Betweenness*, *Eigenvector*.

Surrounding level

At the surrounding level, interactions among people who interact with the individual are included. The clustering coefficient represents the density of interactions around an individual (Watts & Strogatz, 1998). In this study, this coefficient is referred to as *Clustering*. For each individual i , $Clustering_i$ is calculated as the ratio between the actual number of connections among their neighbors and the total possible connections that could exist between them. The equation is given as:

$$Clustering_i = \frac{T_i}{k_i(k_i-1)/2} \quad (3)$$

In this equation, T_i counts how many times two interaction partners of individual i are also connected to each other (forming triangles in the network), while k_i indicates the number of interaction partners that i has.

Furthermore, this study introduced three types of weighted clustering coefficients that consider the weight of interactions. For the weight of interactions between employees, the average daily frequency was used as in the individual scope.

Clustering $w(B)$, developed by Barrat et al., assigns higher weight when sharing many neighbors with people who frequently interact (Barrat et al., 2004). The equation is given as:

$$Clustering\ w(B)_i = \frac{1}{k_i(k_i-1)} \sum_{j, k} \frac{1}{\langle w_i \rangle} \frac{w_{ij} + w_{ik}}{2} a_{ij} a_{jk} a_{ik} \quad (4)$$

In this equation, w_{ij} represents the interaction frequency between i and j , and a_{ij} is 1 when i and j are connected and 0 when not. $\langle w_i \rangle$ represents the expected interaction frequency of i .

Clustering $w(O)$, developed by Onnela et al., evaluates the strength of triangular relationships by calculating the geometric mean of interaction frequencies between an individual and two of their interaction partners (Onnela et al., 2005). The equation is given as:

$$Clustering\ w(O)_i = \frac{1}{k_i(k_i-1)} \sum_{j, k} (w_{ij}w_{jk}w_{ik})^{1/3} \quad (5)$$

In their original paper, Onnela et al. normalized the interaction frequencies $\hat{w}_{ij}$ by dividing them by the maximum frequency in the network, which constrains the coefficient values between 0 and 1. However, since this study focused on the magnitude of the values, not the coefficient itself, w_{ij} was not normalized to apply the same criteria to various organizations.

Finally, *Clustering w(Z)*, developed by Zhang and Horvath, is defined as follows (B. Zhang & Horvath, 2005):

$$Clustering\ w(Z)_i = \frac{\sum_{j, k} w_{ij}w_{jk}w_{ik}}{\sum_{j \neq k} w_{ij}w_{ik}} \quad (6)$$

Like Onnela's measure, the original formulation by Zhang and Horvath used normalized weights, but this study maintained the raw interaction frequencies for the same reason as *Clustering w(O)*. *Clustering w(Z)* calculates a weighted mean where indirect interactions w_{jk} are weighted by the product of direct interactions $w_{ij}w_{ik}$. This approach makes it less sensitive to direct interaction weights while emphasizing indirect interactions more compared with *Clustering w(O)* (Saramäki et al., 2007).

Organizational level

At the organization level, interactions among all connected people within an organization are considered in the definition of centrality. Closeness centrality quantifies an individuals' position in terms of network distances to all other members in the organization (Freeman, 1978). The equation is given as:

$$Closeness_i = \frac{n-1}{\sum_j d(j,i)} \quad (7)$$

Here, $d(j, i)$ represents the minimum number of intermediate connections needed to link individuals i and j , while n indicates the number of people in the interaction network. *Closeness* reaches its maximum of 1 when an individual has direct connections

to everyone else, and decreases toward 0 as network distances increases.

Betweenness quantifies how frequently an individual appears on the shortest paths connecting other pairs of organizational members, reflecting their role as an intermediary in the network (Freeman, 1977). The equation is given as:

$$Betweenness_i = \frac{2}{(n-1)(n-2)} \sum_{j,k} \frac{\sigma_{jk}(i)}{\sigma_{jk}} \quad (8)$$

Here, σ_{jk} represents all possible shortest paths between individuals j and k , while $\sigma_{jk}(i)$ counts only those paths that pass through individual i . The normalization term $2/(n-1)(n-1)$ is included to scale the measure between 0 and 1. Shortest paths are found using Dijkstra's algorithm in *Betweenness*, while weighted version *Betweenness w* uses Dijkstra's algorithm for weighted networks where the inverse of interaction frequency serves as distance.

Eigenvector quantifies an individual's influence in the network, which increases when they are connected to other highly influential members, and is defined by (Bonacich, 1972) as:

$$Eigenvector_i = \frac{1}{\lambda} \sum_j a_{ij} Eigenvector_j \quad (9)$$

Here, a_{ij} indicates the presence (1) or absence (0) of a connection between individuals i and j , while λ represents the Euclidean normalization term for eigenvector. For the weighted version, *Eigenvector w* use interaction frequencies w_{ij} instead of binary connections a_{ij} .

2.2.6. Depression Scores

Depressive symptoms were evaluated using the Center for Epidemiologic Studies Depression (CES-D) scale, a self-report depression scale developed for screening depression in the general population (Radloff, 1977). The questionnaire comprises 20 items written in simple and easily comprehensible language. Among these items, 16 address negative experiences (e.g., “I felt depressed”, “People were unfriendly”) and 4 address positive experiences (e.g., “I was happy”, “I felt hopeful about the future”, “I felt I was just as good as other people”). All 20 items of CES-D are shown in Table 2.2. Participants rate how frequently they experienced each symptom during the past week on a scale of 0 (rarely or none of the time) to 3 (most or all of the time). The composite scores range from 0 to 60, with higher scores suggesting more severe depressive symptoms.

The reliability and validity of the CES-D are well established (Radloff, 1977; Devins et al., 1988; Fountoulakis et al., 2001; Miller et al., 2008; Chin et al., 2015), and it has been utilized in various contexts, including research on the contagion of depressive symptoms through social networks among community populations over 20 years (Rosenquist et al., 2011), as well as in studies related to loneliness as a cross-sectional assessment measure (Elmer & Stadtfeld, 2020). The internal consistency of the CES-D scale was evaluated using Cronbach’s alpha, yielding a value of 0.87 and indicating good reliability among the items. Item-level rating data of the CES-D was available for 371 out of 449 participants for this calculation.

Each employee completed the CES-D once to measure their depressive symptom severity. To ensure unbiased responses, assessment requests were distributed through organizational secretariats, and participants provided responses on paper or Excel files, including their names and wearable device IDs. Completed assessments were sent

directly to the principal investigators, bypassing the secretariats to prevent potential response bias that could arise if participants believed their superiors or secretariat staff would see their answers. The investigators removed names from the responses, retaining only device IDs, and securely disposed of the original documents containing names as confidential information.

Table 2.2 List of CES-D scale items. The scale consists of 16 negative items and 4 positive items (4, 8, 12, and 16) related to depressive symptoms. Each item is scored from 0 to 3 based on how often the respondent felt or experienced it during the past week: 0-Rarely or none of the time (less than 1 day), 1-Some or a little of the time (1-2 days), 2-Occasionally or a moderate amount of time (3-4 days), 3-Most or all of the time (5-7 days). Positive items are reverse-scored.

Index	Item
1	I was bothered by things that usually don't bother me.
2	I did not feel like eating; my appetite was poor.
3	I felt that I could not shake off the blues even with help from my family or friends.
4	I felt I was just as good as other people.
5	I had trouble keeping my mind on what I was doing.
6	I felt depressed.
7	I felt that everything I did was an effort.
8	I felt hopeful about the future.
9	I thought my life had been a failure.
10	I felt fearful.
11	My sleep was restless.
12	I was happy.
13	I talked less than usual.
14	I felt lonely.
15	People were unfriendly.
16	I enjoyed life.
17	I had crying spells.
18	I felt sad.
19	I felt that people dislike me.
20	I could not get "going".

2.2.7. Analysis Methods

To investigate the relationships between network characteristics and depression scores, Spearman's rank correlation coefficient (r_s) was employed, accounting for potential non-linear relationships in the data. The correlation analyses were performed both on the complete dataset and within individual organizational datasets to establish the universality of observed relationships. The overview of correlation analyses is presented in Fig. 2.4.

Correlations were examined across three levels of network characteristics. The individual level included *Degree* and *Weight*. The surrounding level comprised *Clustering*, *Clustering w(B)*, *Clustering w(O)*, *Clustering w(Z)*. The organizational level involved *Closeness*, *Betweenness*, *Betweenness w*, *Eigenvector* and *Eigenvector w*.

The correlation coefficients observed in each of the ten organizations were bootstrapped with 1,000 resamples to obtain confidence intervals. To address the small sample size limitation, bootstrap resampling provided more robust estimates of the true correlation coefficients. The procedure included Fisher z-transformation of these correlation coefficients to normalize their sampling distributions. Weighted mean calculations were then performed to account for different sample sizes across organizations, followed by inverse Fisher z-transformation to calculate confidence intervals. This comprehensive approach enabled us to validate the consistency of relationships between network characteristics and depression scores across diverse organizational contexts.

Statistical significance was set at $p < 0.05$ for all analyses, with 95% confidence intervals reported.

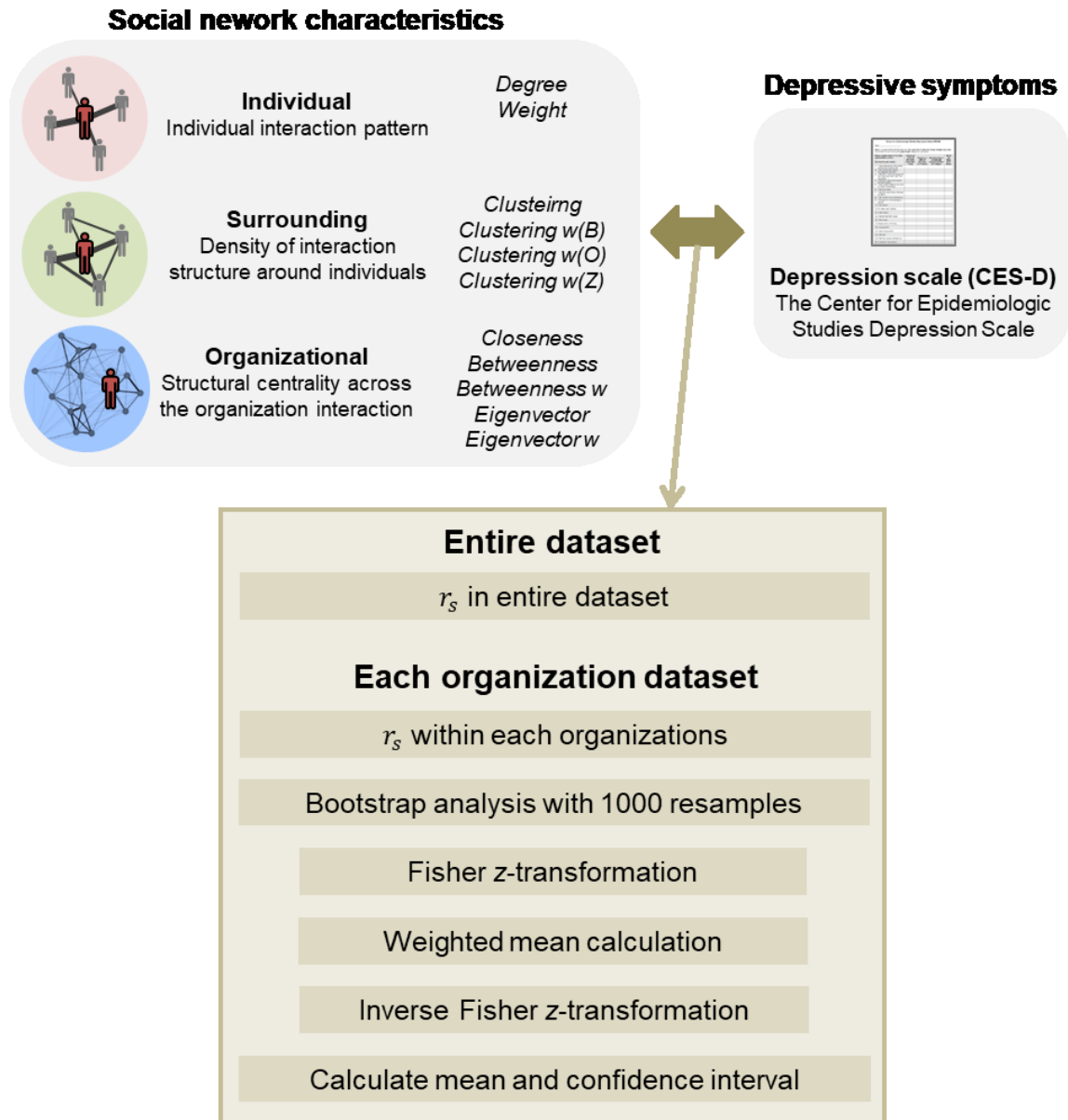


Figure 2.4 Correlation analysis between social network characteristics and depressive symptoms. This study examines correlations between depressive symptoms and quantified network structural characteristics at individual, surrounding, and organizational levels of the social network. Analysis is performed on both the entire dataset and within each organization, with significance testing to determine whether these correlations represent general patterns.

2.3. Results

2.3.1. Individual Level

For individual-level characteristics of the face-to-face interaction network, *Degree* and *Weight* were examined.

The Spearman's rank correlation between these characteristics and depression scores was analyzed for both the entire dataset and within each organization. In Table 2.3, the correlation coefficients calculated from the entire dataset are shown in the first column, with p -values adjusted using the Benjamini-Hochberg method to control for multiple testing errors, including results from other levels. The second column shows results from individual organizations, displaying the mean of 1,000 bootstrap samples of correlation coefficients with 95% confidence intervals indicated in square brackets. Figure 2.5a visualizes these results, where blue dots represent the correlation coefficients from the entire dataset, while X marks and error bars show the bootstrap means and confidence intervals for individual organizations, respectively. Figure 2.5b presents scatterplots with regression lines to provide additional information. Each colored regression line represents the regression results for each organization, while the black dashed regression line shows the results for the entire dataset. These regression lines are shown with 95% confidence intervals derived from 1,000 resampled datasets, where wider intervals indicate regions of sparse data to aid in visual assessment. The same presentation format is applied to analyses at both surrounding and organizational levels.

The correlation analysis at the individual level revealed no significant associations in either the entire dataset or within each organization.

Table 2.3 Spearman's rank correlation coefficients between individual-level network characteristics and depression scores. For each network structural characteristic, the table shows correlation coefficients and p-values (adjusted using the Benjamini-Hochberg method) for the entire dataset, along with mean correlation coefficients and 95% confidence intervals from 1,000 resamples for each organization.

	Entire data	Within each organization
<i>Degree</i>	0.03 ($p = 0.781$)	0.00 [-0.13, 0.10]
<i>Weight</i>	0.02 ($p = 0.797$)	-0.06 [-0.20, 0.05]

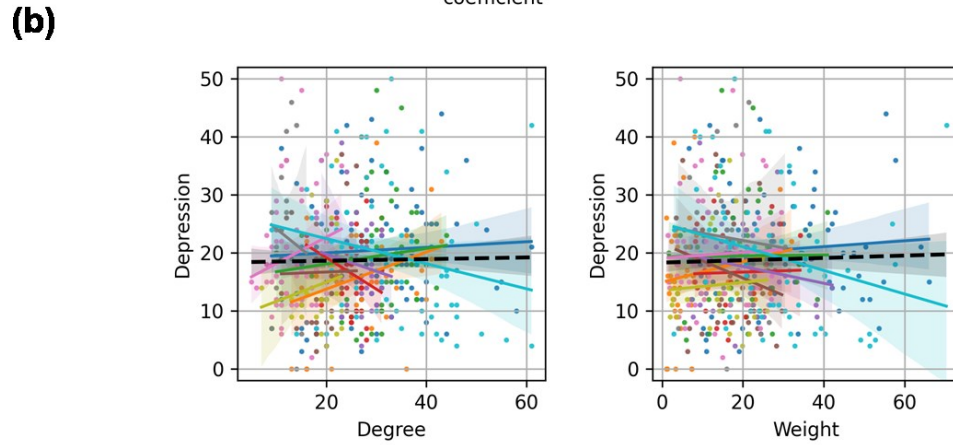
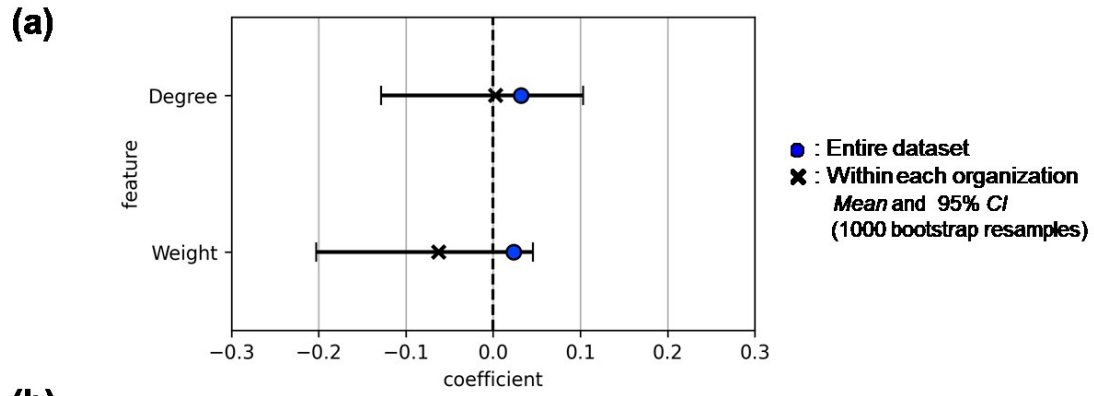


Figure 2.5 Visualization of associations at individual-level analyses. a) Spearman's rank correlation coefficients: entire dataset (blue dots) and each organization (X marks representing mean values from 1,000 bootstrap resamples, with 95% confidence intervals shown as error bars). b) Scatterplots of features versus depression scores, with organization-specific (colored) and overall (black dashed) regression lines: *Degree* (left), *Weight* (right). Shaded area indicates the 95% confidence interval of the regression line of 1,000 bootstrap resamples.

2.3.2. Surrounding Level

For surrounding-level characteristics of the face-to-face interaction network, *Clustering* and three weighted variations were examined: *Clustering w(B)*, *Clustering w(O)*, and *Clustering (Z)*. The results are presented in the same format as the individual-level analysis in Table 2.4 and Fig. 2.6. The significant results are highlighted in red color in Table 2.4 and in bold in Fig. 2.6a.

Clustering and *Clustering w(B)* showed significant negative correlations with depression scores in the entire data ($r_s = -0.16$, $p = 0.004$ and $r_s = -0.18$, $p = 0.001$, respectively). Furthermore, the mean correlation coefficients observed within each organization also demonstrated significant negative trends ($r_s = -0.08$ [95% CI: -0.14 , -0.01] and $r_s = -0.10$ [95% CI: -0.14 , -0.04], respectively). Therefore, these associations indicate that both *Clustering* and *Clustering w(B)* are generally negatively associated with depression scores.

Clustering w(B) demonstrated the strongest correlation among the measures. As *Clustering w(B)* weights the density of interactions by considering the frequency of direct interactions between individuals, this finding suggests that the connection density among frequently interacting individuals played a particularly important role in its association with depression scores.

No general correlations were found in other weighted clustering coefficients. While *Clustering w(O)* showed negative trends within each organization, the correlation was not significant in the entire data. As shown in Fig. 2.6b, the regression lines for *Clustering w(O)* appear relatively misaligned across organizations. This suggests that calculating the geometric mean by multiplying the frequency of direct interactions with neighbors and the frequency of interactions between neighbors is likely to be highly sensitive to interaction patterns and magnitudes across organizations and individuals.

Table 2.4 Spearman's rank correlation coefficients between surrounding-level network characteristics and depression scores. For each network structural characteristic, the table shows correlation coefficients and p-values (adjusted using the Benjamini-Hochberg method) for the entire dataset, along with mean correlation coefficients and 95% confidence intervals from 1,000 resamples for each organization. Values shown in red indicate significant correlations, identified as those with p-values below the established statistical significance level of 0.05 for the entire data analysis, and those with confidence intervals not containing zero for within each organization analyses.

	Entire data	Within each organization
<i>Clustering</i>	-0.16 ($p = 0.004$)	-0.08 [-0.14, -0.01]
<i>Clustering w(B)</i>	-0.18 ($p = 0.001$)	-0.10 [-0.14, -0.04]
<i>Clustering w(O)</i>	-0.02 ($p = 0.797$)	-0.08 [-0.16, -0.01]
<i>Clustering w(Z)</i>	0.01 ($p = 0.797$)	0.00 [-0.08, 0.09]

Meanwhile, *Clustering w(Z)*, which relatively emphasizes the frequency of interactions between neighboring individuals, showed no significant correlations. This suggests that density measures emphasizing the frequency of interactions between surrounding individuals of an individual, which can emphasize interactions between those whom the individual rarely interacts with, is not significant in its relationship with depression scores.

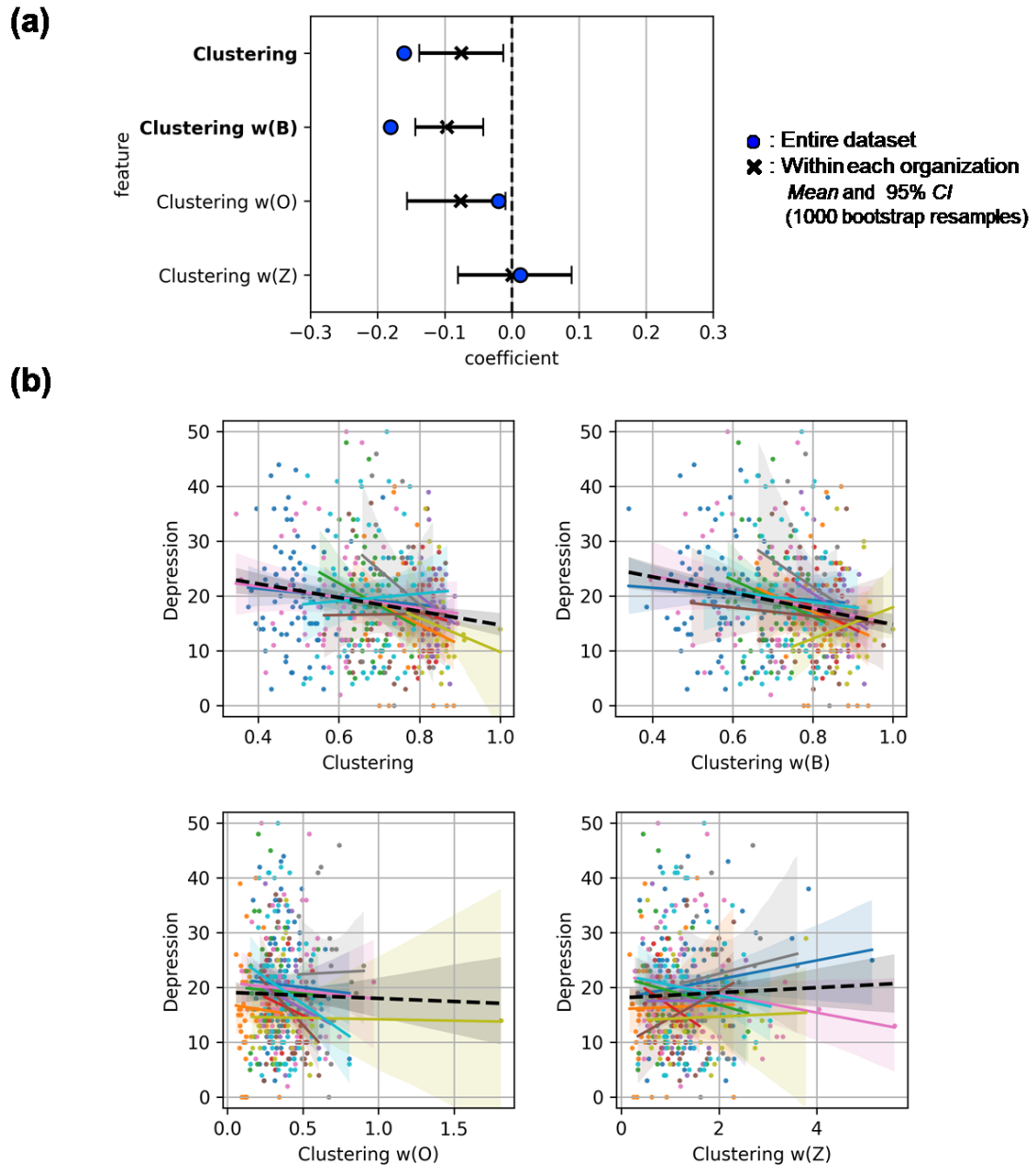


Figure 2.6 Visualization of associations at surrounding-level analyses. a) Spearman's rank correlation coefficients: entire dataset (blue dots) and each organization (X marks representing mean values from 1,000 bootstrap resamples, with 95% confidence intervals shown as error bars). b) Scatterplots of features versus depression scores, with organization-specific (colored) and overall (black dashed) regression lines: *Clustering* (top left), *Clustering w(B)* (top right), *Clustering w(O)* (bottom left), and *Clustering w(Z)* (bottom right). Shaded area indicates the 95% confidence interval of the regression line of 1,000 bootstrap resamples.

2.3.3. Organizational Level

For organizational-level characteristics of the face-to-face interaction network, *Closeness*, *Betweenness*, *Betweenness w*, *Eigenvector*, and *Eigenvector w* were examined. The results are presented in the same format as the individual-level analysis in Table 2.5 and Fig. 2.7.

The correlation analysis at the organizational level revealed no significant associations in either the entire dataset or within each organization. As shown in Fig. 2.7b, organizational-level characteristics demonstrate skewed distributions and vary across organizations, with certain individuals being emphasized at a macro level, and notable variations emerging based on organizational size and structural features.

Table 2.5 Spearman's rank correlation coefficients between organization-level network characteristics and depression scores. For each network structural characteristic, the table shows correlation coefficients and p-values (adjusted using the Benjamini-Hochberg method) for the entire dataset, along with mean correlation coefficients and 95% confidence intervals from 1,000 resamples for each organization.

	Entire data	Within each organization
<i>Closeness</i>	-0.11 ($p = 0.084$)	-0.01 [-0.13, 0.09]
<i>Betweenness</i>	0.01 ($p = 0.797$)	0.02 [-0.09, 0.11]
<i>Betweenness w</i>	-0.04 ($p = 0.691$)	-0.05 [-0.15, 0.03]
<i>Eigenvector</i>	-0.08 ($p = 0.263$)	-0.01 [-0.14, 0.08]
<i>Eigenvector w</i>	-0.05 ($p = 0.625$)	-0.05 [-0.17, 0.04]

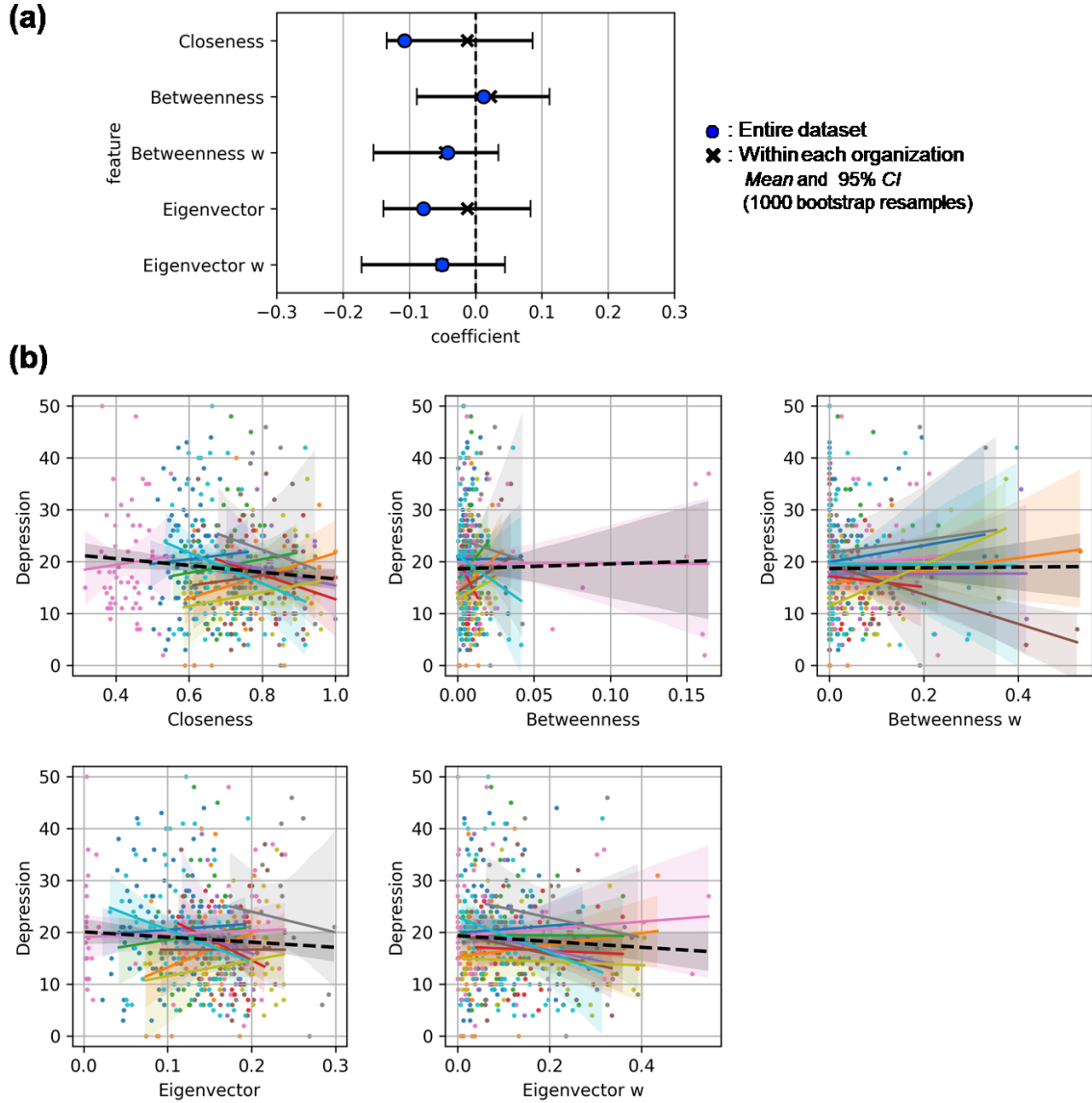


Figure 2.7 Visualization of associations at organization-level analyses. a) Spearman's rank correlation coefficients: entire dataset (blue dots) and each organization (X marks representing mean values from 1,000 bootstrap resamples, with 95% confidence intervals shown as error bars). b) Scatterplots of features versus depression scores, with organization-specific (colored) and overall (black dashed) regression lines: *Closeness* (top left), *Betweenness* (top middle), *Betweenness w* (top right), *Eigenvector* (bottom left), and *Eigenvector w* (bottom right). Shaded area indicates the 95% confidence interval of the regression line of 1,000 bootstrap resamples.

2.4. Discussion

Using face-to-face interaction data observed through wearable devices in real organizational settings, this study quantified the structural characteristics of the interaction network at individual, surrounding, and organizational levels, and investigated their correlation with depressive symptoms. The analysis conducted across the entire dataset and within individual organizations consistently demonstrated that *Clustering* and *Clustering $w(B)$* , which quantify the density of surrounding interaction structure, have a significant negative correlation with depressive symptoms.

These findings emphasize that the importance of surrounding-level face-to-face interaction structures in relation to depressive symptoms. In studies that have investigated network structure centered on individuals using survey methods, the necessity of considering relationship quality has long been discussed (Burt, 1987; Santini et al., 2015). Network density evaluates the structure of cohesive groups, such as when friends of friends are also friends (Granovetter, 1977; Holland & Leinhardt, 1971; Onnela et al., 2007), and has been associated with shared identity and sense of belonging (Coleman, 1988). Studies have shown that a low workplace belongingness, as measured through surveys examining relationships with colleagues, supervisors, and overall workplace relationships, is identified as a significant risk factor associated with depressive symptoms (Cockshaw et al., 2013, 2014). The density of interactions observed through sociometric wearable devices suggests the possibility of capturing interaction patterns related to the sense of belonging.

Research methods based on individual surveys had limitations in constructing structural analyses of relationship quality, due to insufficient data on the interconnections between surrounding individuals. Sociometric wearable devices could offer an effective evaluation method as they provide consistent and comprehensive data collection of organizational

interactions. As a similar example, studies using sociometric wearable devices showed that cohesive local structures in face-to-face interaction networks were associated with employee productivity (Watanabe et al., 2014; Wu et al., 2008). These findings suggest that dense structures of face-to-face interactions captured by wearable devices have positive effects on both functional and psychological aspects of organizational members.

The density of surrounding interaction structure was examined in more detail according to their frequencies, and a stronger correlation was found in *Clustering $w(B)$* , a density measure that assigns higher weights to connections between individuals with whom one frequently interacts. On the other hand, *Clustering $w(Z)$* , which emphasizes the frequencies of indirect interactions (interactions between surrounding people), shows no significant correlation with depressive symptoms. For example, even in cases where one forms a few connections with a highly interactive group, the way *Clustering $w(Z)$* emphasizes indirect interactions overweights the structural density. This density weighting method involving such structural characteristics did not reveal a significant correlation in relation to depressive symptoms. This suggests that merely being connected to a densely interconnected group does not show significant association with depressive symptoms when interactions with that group are infrequent. Along with high-density structures, the impact through the process of direct face-to-face interactions has significant implications for understanding depressive symptoms within organizations.

Meanwhile, no significant associations were observed between depressive symptoms and networks structures at individual and organizational levels. At the individual level, the number of interaction partners and frequency of interactions likely provided insufficient information to capture the qualitative aspects of relationships. The importance of relationship quality has been consistently emphasized in survey-based research (Burt, 1987). For example, it is difficult to distinguish more intimate relationships, and the results likely simply reflect differences in interaction frequencies based on personality or

work-related factors. At the organizational level, structural characteristics are quantified by evaluating indirect benefits obtainable through interactions in which one does not directly participate. For example, if there are benefits transmitted across interaction networks, such as information or influence, the network measures provide different advantages: *Closeness* (Freeman, 1978) offers general advantages by maintaining short distances to all other employees, *Betweenness* (Freeman, 1977) provides exclusive advantages by connecting different individuals within the organization, and *Eigenvector* (Bonacich, 1972) can be advantageous for exercising influence or information diffusion due to connections with individuals in interactively important positions. These advantages can be particularly evident in measurements that consider actual information flow. For instance, a study observing organizational interactions through wearable devices found that *Betweenness* was significantly correlated with productivity only in face-to-face interaction networks during specific task execution, not in long-term observed face-to-face interaction networks (Wu et al., 2008). This suggests that measuring macro-scale advantages requires metrics that better reflect the flow of benefits. Meanwhile, these structural advantages could not be related to depressive symptoms. Social support associated with workplace depressive symptoms has primarily been studied in the context of direct relationships with colleagues and supervisors (Johnson & Hall, 1988; Tennant, 2001; Colligan & Higgins, 2006; Dollard et al., 2007). Furthermore, the preceding discussion, based on the findings of this study, emphasized the significance of frequency in direct interactions, along with network density, as structural factors associated with depressive symptoms. Psychosocial impact from individuals connected through multiple intermediaries could be insignificant in organizational settings.

2.5. Summary

In conclusion, the analysis of comprehensive observations in workplaces involving a variety of occupations shows that the density of face-to-face interactions between surrounding people has a negative correlation with depressive symptoms. Notably, the analysis revealed a stronger correlation with lower depressive symptoms when there were connections between people with whom an individual frequently interacts, suggesting the importance of both interaction density and direct interactions in relation to depressive symptoms. The findings provide quantitative evidence for the importance of surrounding face-to-face interaction structures related to depressive symptoms when observing with sociometric wearable devices.

3. Physical Characteristics Analysis in Face-to-Face Interactions using Wearable Device and Depressive Symptoms

3.1. Aim

As introduced in Section 1.2.2, reduced physical movement and impaired behavioral coordination during interactions are associated with depressive symptoms among interacting individuals. Furthermore, as discussed in Section 2.4, among social network density measures, the frequency of direct face-to-face interactions emerged as significant associated with depressive symptoms, calling for a deeper understanding of the direct face-to-face interaction processes.

This study investigated the association between physical movement patterns during face-to-face interactions and depressive symptoms in both individuals and their interaction partners. Considering the logging frequency set at one-minute intervals for long-term observation and the variability of face-to-face interaction durations in uncontrolled real-world settings, this study focused on physical movement patterns as indicators of general tendencies in movement characteristics during interactions, rather than coordination effects like synchronization. Features of physical movement were extracted to capture the degree of physical activation and participation during face-to-face interactions, such as nodding, gesturing, and arousal, and refer to this as ‘physical engagement’. Physical engagement was calculated for each individual across their interactions to analyze the relationship between physical engagement levels and depressive symptoms for both the individuals and their interaction partners. Additionally, due to the variability in the number of interaction partners across individuals (i.e., some interact with many while others with few) in real-world settings, this study refined the

analysis by focusing on primary interaction partners to better observe the patterns and strength of these relationships. Even when controlling for the number of primary interactors, some individuals can have greater influence as they serve as primary interaction partners to multiple others in network settings. These influential individuals were defined as key interaction partners and their characteristics were investigated. Finally, the implications of these results within complex interaction networks were discussed.

3.2. Methods

3.2.1. Description of Data

This study analyzed face-to-face interaction data from ten Japanese organizations collected by the World Signal Center, Hitachi, Ltd. in 2009. This dataset is identical to Section 2.2, and the process of adjusting for possible misalignment and excluding participants with insufficient usage period for reliability follows Section 2.2.3. An empty interval criterion of less than 5 minutes was applied for reasonable counting of interactions. Employees who had a record of wearable device use of less than 5 hours or face-to-face interaction time of less than 1 hour were excluded from the analysis. This resulted in a final dataset of 449 employees, including the face-to-face interactions data from wearable device and depression scores from CES-D.

3.2.2. Measurement of Body Rhythm

The wearable device (Business microscope, Hitachi, Ltd., Japan) is equipped with a tri-axial accelerometer to capture the physical movements of the wearer's upper body. The accelerometer measures acceleration along three orthogonal axes at a sampling rate of 50 Hz. The measured tri-axial accelerations were converted into a single acceleration value using the Euclidean norm. The number of points at which this norm acceleration value crossed its mean was counted every 10 seconds, and the average of six measurements (1 minute) was calculated. This study refers to this frequency as the body rhythm.

Body rhythm effectively captures periodic and patterned physical activities, rather than simply measuring strong directional or transient and intense movements that can be influenced by individual physical characteristics such as body size. While it cannot precisely identify individual movements, typical ranges have been observed: running (over 4 Hz), excited discussion or rushed walking (3–4 Hz), walking, talking with dynamic gestures (2–3 Hz), talking or typing (1–2 Hz), web browsing or listening (0–1 Hz), sleeping, or thinking without movement (0 Hz) (Ara et al., 2009).

3.2.3. Physical Engagement during Face-to-Face Interaction

Face-to-face interactions involve various forms of physical engagement, such as nodding in agreement, using gestures, synchronizing movements with others, and showing bodily responses according to emotional arousal levels. Although these physical movements can be reflected through body rhythm measurements taken every minute, the purpose was not simply to measure physical movement patterns during interaction, but rather to quantitatively evaluate the amount of physical engagement caused by interaction, excluding influences unrelated to the interaction itself. To quantify such physical engagement during face-to-face interactions, this study defined physical engagement as follows:

$$PE_i(k) = \overline{BR_i(t)}_{t \in T_k} - \overline{BR_i(t)}_{t \in \widehat{T_k}} \quad (10)$$

In this equation, $PE_i(k)$ is the physical engagement of individual i during face-to-face interaction k , $BR_i(t)$ is the body rhythm of i at time t , T_k is the set of time points that comprise interaction k , and $\widehat{T_k}$ is the set of time points that occurred within 30 minutes preceding interaction k . The overbar denotes the mean of the respective values. The baseline body rhythm is removed by subtracting $\overline{BR_i(t)}_{t \in \widehat{T_k}}$, which represents the average rhythm before interaction k . By subtracting the average body rhythm before the interaction, physical engagement attributable to the face-to-face interaction can be identified, excluding factors embedded in pre-interaction body rhythm. Fig. 3.1a shows an example of actual body rhythm before and during a face-to-face interaction, as measured by wearable devices.

When defining the onset of interactions, it was observed that body rhythms tend to increase approximately 10 minutes before and after interactions detected by infrared module wearable within wearable device (see Appendix C). This pattern can result from pre-interaction movements or preparation activities. Alternatively, it can capture

unrecorded social interactions such as greetings or conversations that occur when participants are mutually aware of each other but their sensors aren't yet properly aligned for detection. Although interactions were corrected for misalignment during preprocessing, the onset and termination of interactions remained susceptible to misalignment issues. Given the observed elevation in Body Rhythm during these periods, this study extended T_k to include 10-minute windows before and after each interaction and shifted the baseline period $\widehat{T}_k$ to 10 minutes prior to its original time point.

The baseline measurement becomes problematic when the same interaction partner appears in the baseline window before interaction k . To solve this problem, these consecutive interactions with the same partner were combined into one single interaction event, thus removing the partner's presence from the baseline period. While this method addresses interactions with the same partner, it does not account for interactions with other individuals during the baseline period. The data shows that each 30-minute baseline window contained interactions with other individuals, averaging 4.13 encounters with a median of 1. Considering that the choice of baseline window span could affect the results, the robustness of the findings was demonstrated by confirming that the 30 min setting did not significantly impact the main findings of this study within spans ranging from 10 to 60 min in Appendix B.

To validate that physical engagement effectively captures the increased body movements during social interactions, this study examined the difference between employees' body rhythms during interaction windows and their baseline measurements. Body rhythms were measured during both baseline and interaction periods for all observed interactions.

The distribution of body rhythms during both interaction and baseline for all observed interactions is visualized using kernel density estimation (Fig. 3.1b). The mean physical rhythm during interaction was 1.36 (SD = 0.59), which was higher than the baseline mean

of 1.10 (SD = 0.60), and this difference was confirmed to be significant by a one-tailed paired t-test ($t(53,761) = 99.60, p < 0.001$). Regarding the normality assumption of the t-test, the difference between interaction and baseline physical rhythm showed a mean of 0.26 and median of 0.24, with a skewness of 0.01 indicating near-symmetry. While the kurtosis of 0.97 indicated a flatter distribution compared to the normal distribution (3), Q-Q plot analysis showed data points closely aligned with the ideal normal distribution line in the central region, with minor deviations only at the extremes (Appendix D), supporting the satisfaction of the normality assumption. This significant increase in body rhythms during the interaction phase suggest that physical engagement, quantified as the difference in mean body rhythm between the interaction and baseline windows, captures the interaction-induced body movements.

While physical engagement metric is expressed in Hz, interpreting it directly as a frequency requires caution. Rather, it captures the elevated body rhythm activity that emerges in the context of face-to-face interactions.

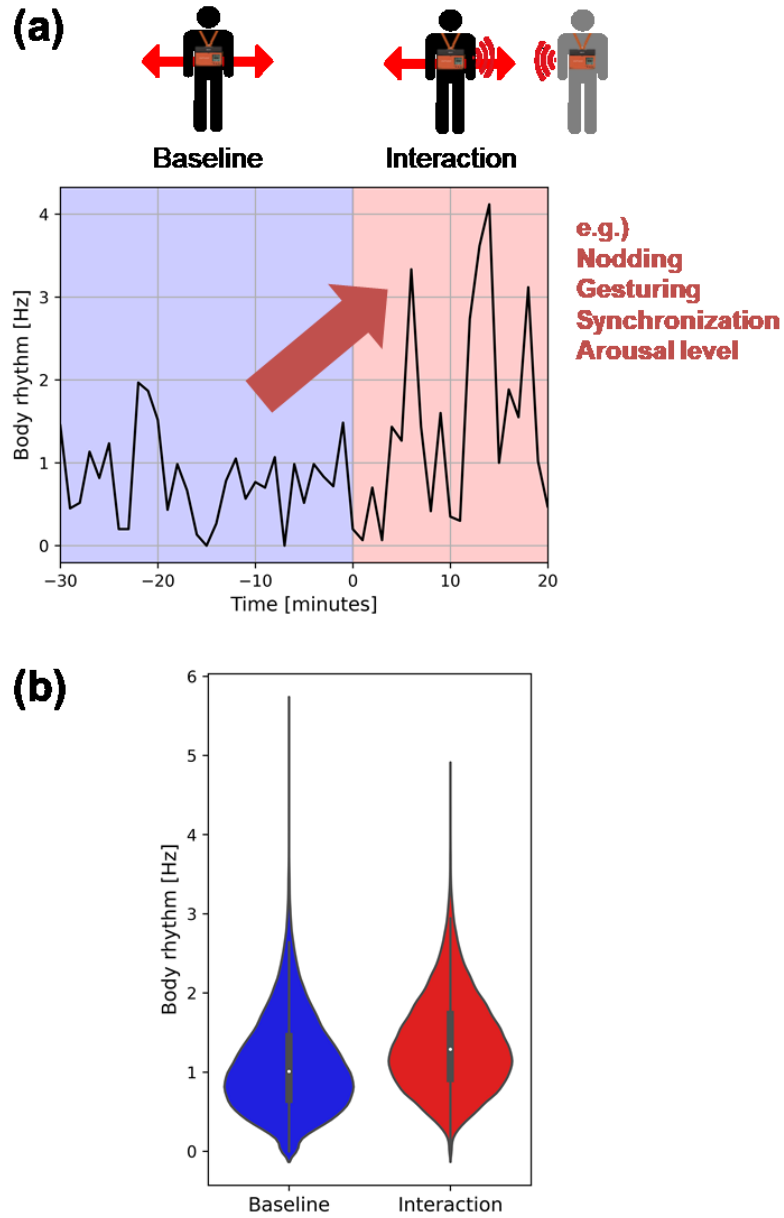


Figure 3.1 Body rhythms during face-to-face interaction. a) An example of body rhythms before and during a face-to-face interaction phase detected through wearable devices. b) Distribution of mean body rhythms during baseline and interaction windows for each observed face-to-face interaction.

3.2.4. Characteristics of Face-to-Face Interactions of an Employee

To synthesize patterns of interactions observed from individuals, this study averaged the characteristics observed in interactions involving these employees. First, the characteristics observed in an interaction are as follows:

$$F_{i,j}(k) = [PE_i(k) \quad PE_j(k) \quad DS_i \quad DS_j] \quad (11)$$

In this equation, $F_{i,j}(k)$ denotes the observed characteristics of interaction k between employees i and j , $PE_i(k)$ indicates the physical engagement of individual i during face-to-face interaction k , DS_i represents individual i 's depression score, with $PE_j(k)$ and DS_j indicating the corresponding measures for individual j .

The characteristics of face-to-face interactions for employee i are defined as the mean of all observed $F_{i,j}(k)$ values involving employee i , formulated as:

$$\overline{F_{i,p_i(k)}(k)}_{k \in I_i} = \left[\overline{PE_i(k)}_{k \in I_i} \quad \overline{PE_{p_i(k)}(k)}_{k \in I_i} \quad DS_i \quad \overline{DS_{p_i(k)}}_{k \in I_i} \right] \quad (12)$$

In this equation, $p_i(k)$ denotes the interaction partner of employee i in interaction k , I_i represents the set of interactions involving employee i , and $\overline{F_{i,p_i(k)}(k)}_{k \in I_i}$ indicates the mean characteristics of face-to-face interactions for employee i . The overbar notation represents the average of the corresponding values. For DS_i , since it was measured only once, the mean value equals the single measured value.

3.2.5. Analysis Methods

To investigate the association between physical engagement and depression scores of both individuals and their interaction partners, a comprehensive analysis was conducted on the associations between physical engagement and depression scores using the characteristics of face-to-face interactions ($\overline{F_{i,p_i(k)}(k)}_{k \in I_i}$) of an Employee dataset.

Specifically, four associations were examined: (1) the association between an individual's physical engagement ($\overline{PE_i(k)}_{k \in I_i}$) and their own depression scores (DS_i), (2) the association between an individual's physical engagement ($\overline{PE_i(k)}_{k \in I_i}$) and their partners' depression scores ($\overline{DS_{p_i(k)}}_{k \in I_i}$), (3) the association between partners' physical engagement ($\overline{PE_{p_i(k)}(k)}_{k \in I_i}$) and the individual's depression scores (DS_i), and (4) the association between partners' physical engagement ($\overline{PE_{p_i(k)}(k)}_{k \in I_i}$) and their own depression scores ($\overline{DS_{p_i(k)}}_{k \in I_i}$). These analyses comprehensively evaluate the associations between depression scores and physical engagement levels of individuals and their partners during face-to-face interactions. Figure 3.2 shows an overview of the characteristics of face-to-face interactions and the associations between depression scores and physical engagement of employee i and the interaction partners of i .

To examine these associations, Pearson's correlation analyses were conducted, assessing the strength, direction, and statistical significance of associations. Prior to conducting correlation analyses, scatterplots were examined to verify the assumptions of linearity and absence of outliers. Visual inspection of the scatterplots confirmed that the relationships between variables were approximately linear and no extreme outliers were identified (Fig. 3.3). Additionally, Appendix E validates that the results were robust in response to outliers or nonlinearity by using Spearman's correlation coefficient. Two-tailed tests were performed for correlation analysis. Statistical significance was set at $p < 0.05$ for all analyses.

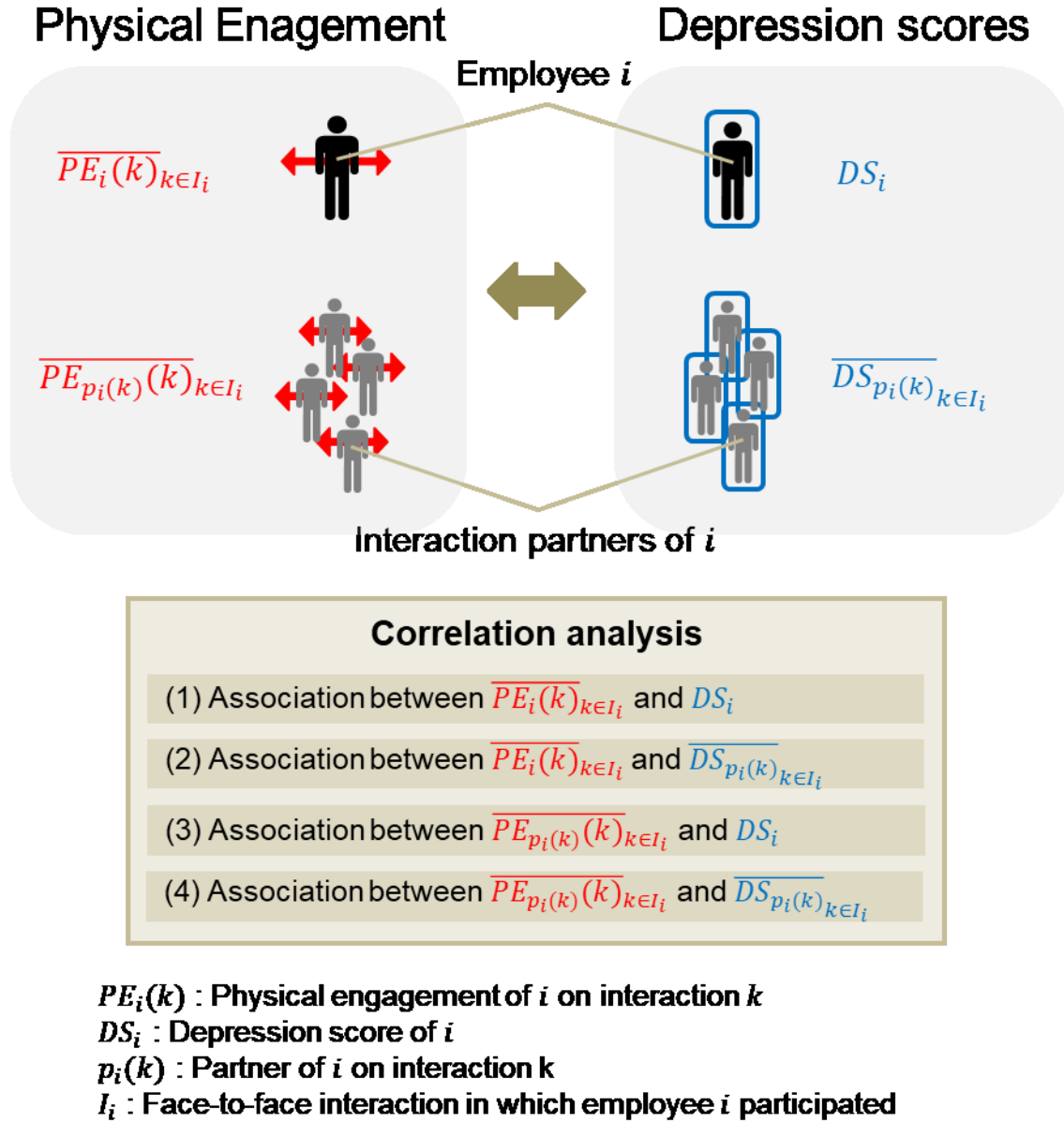


Figure 3.2 Overview of the characteristics of face-to-face interactions and the associations between physical engagement and depression scores of employee i and the interaction partners of i . Average values of physical engagement and depression scores for both the focal employee and their partners were calculated from observed interaction data of employee i . All possible correlations between depression scores and physical engagement were examined to investigate the patterns of how these two variables are associated during interactions observed from employee i .

3.3. Results

3.3.1. Associations between Physical Engagement and Depression Scores with Interaction Partners

Correlations were investigated between physical engagement and depression scores of both self and partners. Fig. 3.3 presents scatter plots and correlation analyses of the associations between physical engagement and depression scores among individuals and their partners. The correlation analyses show no significant correlation between employees' average physical engagement and their depression scores ($r = -0.04$, $p = 0.356$; Fig. 3.3a). Meanwhile, an employee's average physical engagement demonstrates a significant negative correlation with the average depression scores of the partners in their face-to-face interactions ($r = -0.25$, $p < 0.001$; Fig. 3.3b). A relatively weaker but still significant negative correlation was also observed between the average physical engagement of partners in face-to-face interactions and the depression score of an employee ($r = -0.10$, $p = 0.041$; Fig. 3.3c). Despite not including measurements from the target employees, a significant negative correlation was also found between partners' physical engagement and their depression scores in face-to-face interactions ($r = -0.27$, $p < 0.001$; Fig. 3.3d). These findings suggest that employees' physical engagement shows negative associations with their interaction partners' depressive symptoms, and this negative association is also observed among their surrounding interaction partners.

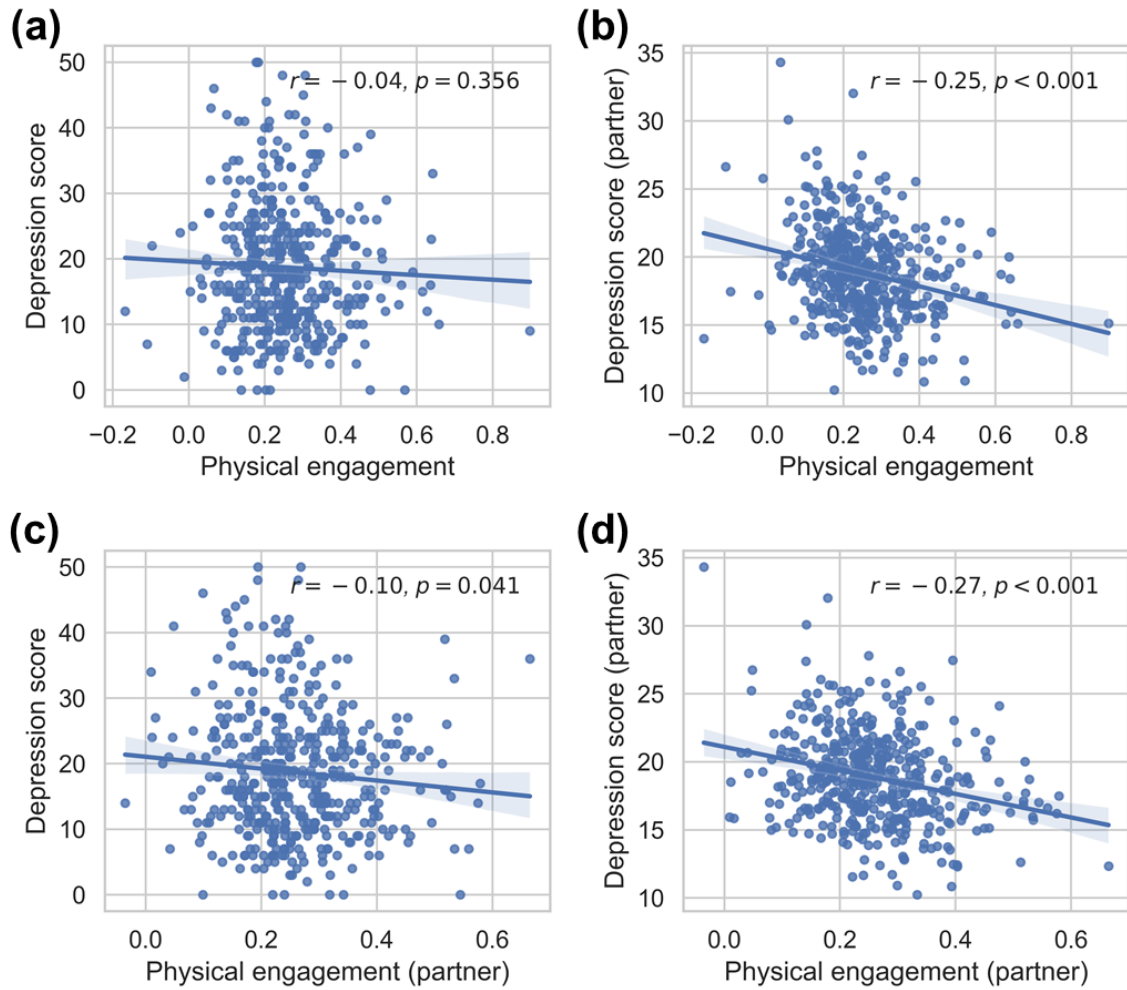


Figure 3.3 Associations between physical engagement and depression scores. The scatter plots show correlations between (a) individual's physical engagement and their own depression scores, (b) individual's physical engagement and partners' depression scores, (c) partners' physical engagement and individual's depression scores, and (d) partners' physical engagement and their own depression scores. r and p represent Pearson correlation coefficients and statistical significance, respectively. Linear regression lines are shown with 95% confidence intervals derived from 1,000 resampled datasets, where wider intervals indicate regions of sparse data to aid in visual assessment.

3.3.2. Associations between Physical Engagement and Depression Scores with Primary Interaction Partners

Unlike experimental settings, face-to-face interaction networks can involve interactions with a variable number of people. As the number of interactions varies among individuals, with some interacting with many others while others with few, the resolution at which the correlations between physical engagement and depression scores with interaction partners emerges remains unclear.

To identify the correlations at a refined resolution, this analysis controlled the number of primary interaction partners of each employee. The primary interaction partners are ranked by interaction frequency, and the same correlation analyses as in Section 3.3.1 were performed on interactions with primary interaction partners. Only original partners were included when the adjusted number of partners exceeded the original number. The numbers of partners observed among employees show the following statistics: $M = 24.06$, $SD = 10.11$, $min = 4$, $max = 60$.

Figure 3.4 shows correlations examined by adjusting the number of primary interaction partners. The overall correlations are observed to stabilize once approximately five primary interaction partners are included, which indicates that the majority of observed interactions are concentrated among a small number of key partners, highlighting the significance of interaction patterns with these individuals in the correlations. The analysis reveals significant negative correlations emerging at different thresholds: between individual's physical engagement and partners' depression scores at two primary partners ($r = -0.12$, $p = 0.008$; Fig. 3.4b), between partners' physical engagement and their own depression scores at three partners ($r = -0.15$, $p = 0.001$; Fig. 3.4d), and between partners' physical engagement and individual's depression scores at eight partners ($r = -0.09$, $p = 0.049$; Fig. 3.4c). Furthermore, confidence interval analysis of correlation coefficients

obtained from each organization revealed significant negative trends in correlations between individual's physical engagement and partners' depression scores at two primary partners ($r = -0.08$ [95% CI: $-0.19, -0.004$]), and between partners' physical engagement and their own depression scores at three partners ($r = -0.09$ [95% CI: $-0.20, -0.004$]). The methodology for analyzing confidence intervals across organizations follows the same procedure described in Section 2.2.7: bootstrap resampling with Fisher z-transformation and weighted mean calculations to account for organizational differences in sample sizes.

In summary, the significant correlations between physical engagement and depression scores observed in employee-partner interactions are robust even when examining interactions with two (physical engagement – partners' depression score) and three (partners' physical engagement – partners' depression score) primary partners.

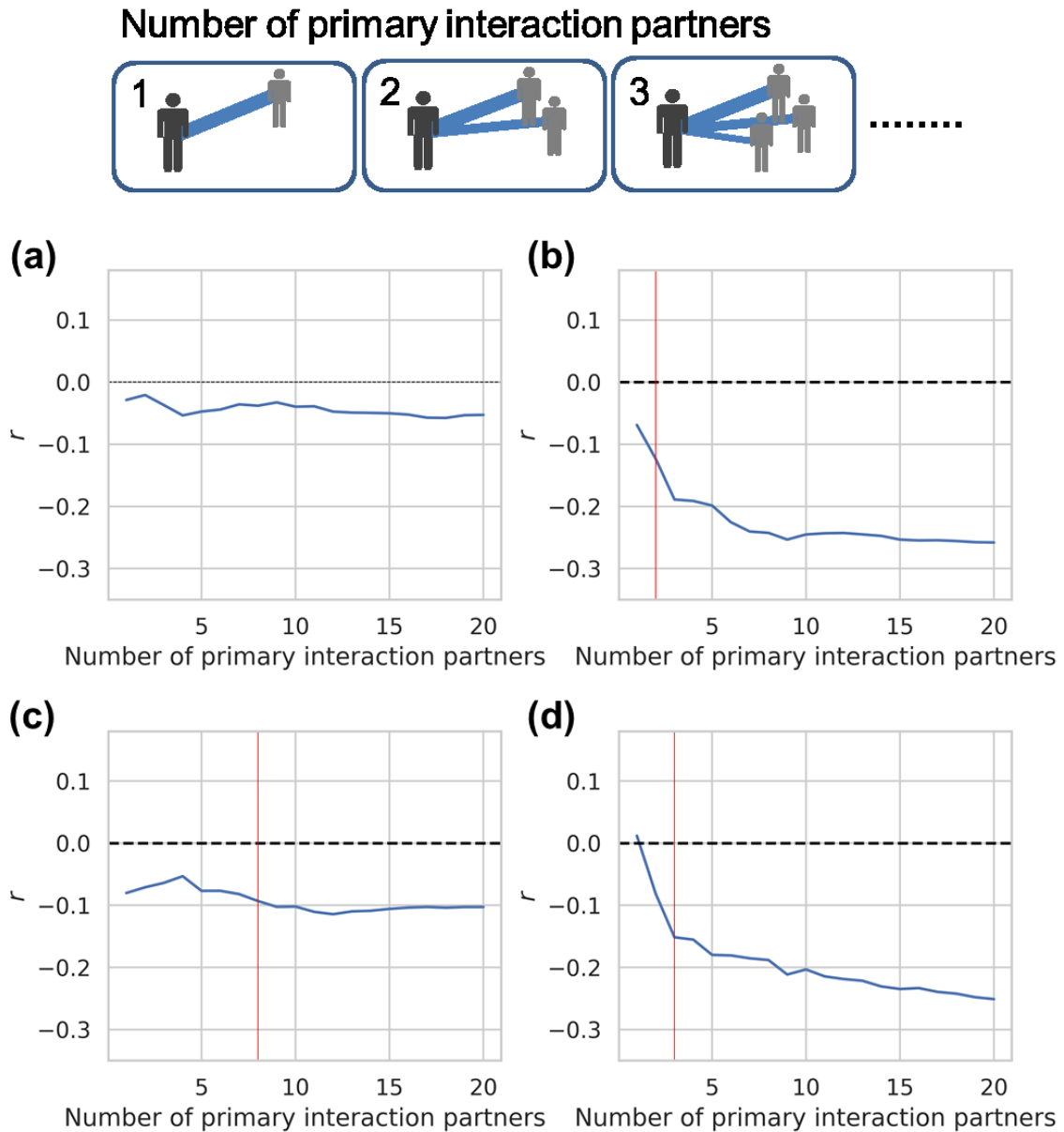


Figure 3.4 Associations between physical engagement and depression scores when controlling the number of primary interaction partners. The plots show correlations when controlling the number of primary interaction partners between (a) individual's physical engagement and their own depression scores, (b) individual's physical engagement and partners' depression scores, (c) partners' physical engagement and individual's depression scores, and (d) partners' physical engagement and their own depression scores. Red lines indicate the number of primary interaction partners at which the observed correlations become significant.

3.3.3. Characteristics of Key Interaction Partners within Organizations

The findings in Section 3.3.2 demonstrate that the characteristics of face-to-face interactions with primary interaction partners play a significant role in the correlations between physical engagement and depression scores. However, these primary interaction partners of individuals can be repeatedly selected by different individuals within the complex face-to-face interaction network in organizations. Specifically, individuals who frequently interact with diverse people are more frequently included in face-to-face interactions of individuals within organizations. Therefore, their characteristics are influential in determining the relationship between physical engagement in organizational interactions and depression scores.

This study refers to these individuals as key interaction partners. To identify them, the top three interaction partners for each employee were selected based on interaction frequency. This threshold of three was established as the main correlations between physical engagement and depression scores with interaction partners became statistically significant at this number when controlling for primary interaction partners (Section 3.3.2), allowing us to identify key interaction partners repeatedly selected across the network. Next, the number of times each employee was selected as a primary interaction partner within their workplace was aggregated. Using the tertile method, employees were categorized into three groups (high, middle, and low) based on their frequency of being selected as primary interaction partners, which reflects the importance of their interactions in the organization. While the tertile method does not provide clear boundaries that distinctly separate the groups, it effectively enables comparison of interaction importance by creating three similarly-sized groups. This resulted in high ($n = 115$), middle ($n = 130$), and low ($n = 204$) groups, with the upper group consisting of those above the tertile points.

This study defined this high group as key interaction partners, and for all three groups (high, middle, and low), the correlations between physical engagement and depression scores were examined using the same methodology as described in Sections 3.3.1 and 3.3.2.

Correlation analysis revealed significant negative correlations between all physical engagement measures and depression scores in the key interaction partners (high) group: correlation between physical engagement and depression score ($r = -0.20, p = 0.034$; Fig. 3.5a), physical engagement and depression score (partner) ($r = -0.23, p = 0.013$; Fig. 3.5b), physical engagement (partner) and depression score ($r = -0.22, p = 0.019$; Fig. 3.5c), and physical engagement (partner) and depression score (partner) ($r = -0.24, p = 0.009$; Fig. 3.5d). These results demonstrate a prominent interplay in face-to-face interactions centered on key interaction partners, where the physical engagement and depression scores show significant negative associations in both key interaction partners and their interaction partners.

Meanwhile, significant negative correlations were consistently observed across all groups between physical engagement and depression score (partner) (Fig. 3.5b, f, j), and between physical engagement (partner) and depression score (partner) (Fig. 3.5d, h, l), which were identified as significant in Sections 3.3.1 and 3.3.2. This confirms the robustness of the findings in Sections 3.3.1 and 3.3.2, and suggests that these associations represent general patterns in face-to-face interactions among employees within organizations.

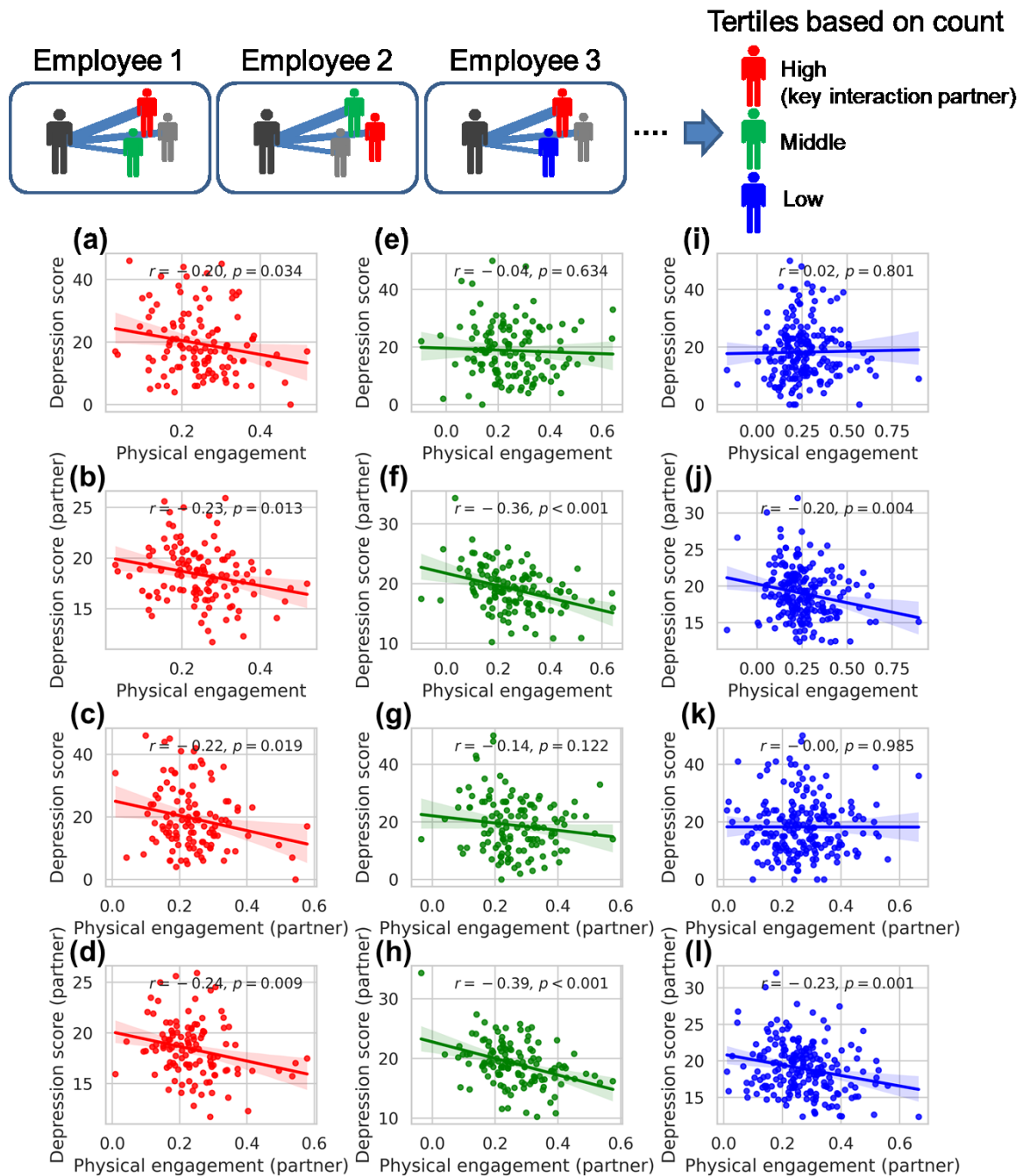


Figure 3.5 Associations between physical engagement and depression scores in three groups (high, middle, and low) categorized by the importance of their interactions within the organization. The associations are shown in panels a-d (high; red), e-h (middle; green), and i-l (low; blue). The line represents the linear regression line, and the shaded area indicates the 95% confidence interval of the regression line of 1,000 bootstrap resamples.

3.4. Discussion

This study investigated how physical engagement during interactions measured through wearable devices, is associated with depressive symptoms of both individuals and their interaction partners in organizational settings. The analysis revealed a significant negative correlation between employees' physical engagement during interactions and their partners' depression scores. A weaker but significant negative correlation was also found between employees' depression scores and their partners' physical engagement. Additionally, despite not including measurements from the focal employees, physical engagement of interaction partners showed a negative correlation with their depression scores. To investigate these correlations in more detail, considering the complexity of interactions measured in real workplace settings, additional analyses were conducted by controlling for the number of interaction partners based on interaction frequency. The analyses confirmed the significant correlation between physical engagement and partners' depression scores even when limiting the number of partners to two (three for correlation between partners' physical engagement and partners' depression scores). Furthermore, the characteristics of key interaction partners who appear frequently as interaction partners of other employees were examined, considering their greater influence on the observed correlations. The analysis revealed significant negative correlations in all possible pairings of physical engagement and depression scores between key interaction partners and their interaction partners, suggesting a significant negative interplay between physical engagement and depression scores around these key interaction partners.

Several points warrant discussion regarding the interpersonal relationships between physical engagement and depression scores. First, the negative correlation observed between employees' physical engagement and partners' depression scores (Fig. 3.3b) is consistently confirmed under various conditions: when controlling for the number of

primary partners (Fig. 3.4b), across different organizations, and among the high, middle, and low groups (Fig. 3.5b, f, j) defined by their importance as interaction partners within the organization. This consistent negative correlation suggests that the manner in which employees physically engage in face-to-face interactions would be more closely related to the depressive symptoms of those they interact with. While causal interpretations are limited, several possibilities can be considered: frequent interactions with depressed employees lead to decreased physical engagement, deficient physical engagement negatively impacts partners' experiences, or structural and contextual factors are involved.

The significant negative correlation between partners' physical engagement and partners' depression scores in face-to-face interactions presents an intriguing paradox (Fig. 3.3d). The correlation between physical engagement and depression scores is absent among individuals (Fig. 3.3a) but emerges when individuals are included as interaction partners for others. One possible explanation is that the correlation could be the result of overrepresentation of the characteristics of key interaction partners. Among key interaction partner groups, a significant correlation was found between their own physical engagement and their own depression scores (Fig. 3.5a). This correlation of key interaction partners, frequently included in other employees' interaction partners, would have contributed to the observed negative correlation (Fig. 3.3d), and the initial steep rise in the correlation coefficient when controlling for the number of primary partners (Fig. 3.4d). Another possible explanation is that the results include the characteristics of the group in which the employees frequently interacted. The correlation between one's physical engagement and their interaction partners' depression scores could manifest as a group correlation among those who frequently interacted with each other. As the number of primary interaction partners included in the analysis increased, the gradually rising correlation coefficient between partners' physical engagement and partners' depression

scores likely captures the group structure (Fig. 3.4d). Future studies considering the structure could deepen the understanding of these potential explanations.

The correlation between employees' depression scores and their partners' physical engagement (Fig. 3.3c) was weaker than that between employees' physical engagement and their partners' depression scores (Fig. 3.3b). One possible mechanism is that depressive symptoms reduce the physical engagement of interaction partners. In such cases, depressive symptoms of interaction partners could have a stronger effect on reducing one's own physical engagement, compared to the effect of one's depressive symptoms on interaction partners' physical engagement, because the interaction partners are also influenced by their interaction with other employees. This possibility is partially supported by the negative correlation between depression scores of individuals and interaction partners' physical engagement among key interaction partners (Fig. 3.5c), as these key interaction partners are primary interaction partners of their interaction partners. Additionally, in cases where physical engagement influences partners' depressive symptoms, there is a limitation in measurement resolution as depressive symptoms are not measured for each interaction. To verify this mechanism, longitudinal observation of changes or the introduction of quantifiable emotional state indicators for each interaction would allow for more accurate interpretation.

While physical engagement during interactions is correlated with partners' depressive symptoms, for individuals who hold important positions as interaction partners within the organization, physical engagement was also associated with their own depressive symptoms (Fig. 3.5a). This finding provides several interpretations regarding the mechanisms between physical engagement and depressive symptoms. First, it can reflect the impact of accumulated unsatisfactory interaction experiences. Behavioral engagement during interactions, such as synchronization with interaction partners, is known to facilitate the formation of relationships and smooth communication (Bernieri, 1988; Chartrand &

Bargh, 1999). Previous research has suggested that impairments in such nonverbal interactions could serve as a mechanism inducing depression, associated with an increase in unsatisfactory and stressful interpersonal events (E. H. Bos et al., 2007). Such discussions have primarily focused on individuals exhibiting depressive symptoms but are also relevant to their interaction partners, given the reciprocal nature of face-to-face interactions. Low physical engagement observed through wearable devices could reflect impaired nonverbal interactions, with its severity potentially influenced by the depressive symptoms of interaction partners. The accumulation of such interactions could have a negative impact on interaction experiences, especially for key interaction partners within the organization. Second, the role of physical engagement in the emotional contagion process can be considered. Physical movements such as facial and bodily expressions during interactions are known to synchronize with those of interaction partners and serve as a mechanism for coupling emotional states between individuals (Paz et al., 2022). This study found that employees' physical engagement shows a negative correlation with their partners' depressive symptoms (Fig. 3.3b). This reduced physical engagement could be an adjusted result in response to their partners' depressive symptoms, and particularly for key interaction partners, this adjustment could also be associated with their own depressive symptoms (Fig. 3.5a), suggesting the possibility of emotional contagion or reception centered on these individuals. These interpretations highlight that reduced physical engagement associated with partners' depressive symptoms could be related to impaired interactions or emotional contagion, and individuals occupying significant positions in organizational interactions could be particularly vulnerable to these effects, or vice versa.

This study's findings have significant implications for workplace applications that extend beyond individual-focused approaches. This study highlights the potential for observing and addressing workplace depressive symptoms through measuring face-to-face interactions using sociometric wearable devices. High-quality interactions among

employees, as well as the creation of environments that facilitate such interactions, have been recognized as crucial in organizational management, particularly for fostering task performance and innovation (R. L. Cross & Parker, 2004; Gratton, 2007; Owens et al., 2016). The benefits derived from interpersonal interactions have often been conceptualized in terms of “energy” (R. L. Cross & Parker, 2004; Owens et al., 2016), which is associated with positive psychological resources and ability to cope with stress (Braha & Karabulut, 2024). From this perspective, interactions within an organization can be a factor that increases or decreases a person’s energy in relation to the work. Similarly, this study observed reduced physical engagement among individuals interacting with colleagues who exhibit high levels of depressive symptoms. Although cognitive and physical energy represent distinct concepts, future research could investigate the relationship between these two forms of energy.

3.5. Summary

In conclusion, this study investigated how physical engagement and depressive symptoms are associated between face-to-face interaction partners within organizations. To examine this, physical engagement during face-to-face interactions and depression scores were measured from 449 employees in 10 workplaces across various industries. The findings reveal that employees' depressive symptoms are negatively associated with the physical engagement of their interaction partners, and for those in key organizational positions, physical engagement is associated with both their interaction partners' and their own depressive symptoms. These findings highlight the importance of including interaction partners and considering their organizational influence in observing and understanding the dynamics of depressive symptoms within organizations.

4. General Discussion

4.1. Comprehensive Discussion of Results

The findings of this study highlight the importance of direct face-to-face interactions in relation to depressive symptoms within organizations. Results from Chapter 2 confirm that depressive symptoms are associated with structural characteristics at the surrounding level, and also confirm the importance of frequent face-to-face interactions within such group structures. Chapter 3 provides evidence from individual interaction patterns, demonstrating that employees' physical engagement during face-to-face interactions decreases when employees around them show higher depressive symptoms. For key interaction partners in organizations, this physical engagement also correlates with their own depressive symptoms. Together, these findings suggest that employees' depressive symptoms are linked to how frequently and actively one engages in face-to-face interactions with other employees, along with group structures or key positions in interactions within the organization.

In organizations, interactions are not only social relationships but are also intertwined with work-related communication. Therefore, quantitative analysis limited to observable interaction patterns may not provide sufficient insight. Recent wearable device studies have demonstrated that interactions contain qualitative aspects beyond just observable frequencies and durations of contact (Higo et al., 2014; Ogata et al., 2017; Xu et al., 2013). Studies have shown that people show increased frequency of body rhythms during face-to-face interactions, and their activation levels are similar to those of their interaction partners (Higo et al., 2014), also with synchronous patterns in the direction of these changes (Ogata et al., 2017). Furthermore, in community structures with dense interactions, higher similarities in body rhythms were observed during interactions (Xu et al., 2013), suggesting that interactions within frequently communicating groups can be

qualitatively different in non-verbal aspects. Together with these studies, the findings of this research emphasize the importance of comprehensive observation to monitor the qualitative patterns of interactions, including who interacts with whom and how, and suggest that such characteristics can help in observing and understanding depressive symptoms in organizational settings.

4.2. Significance of Interactions within Surrounding and Primary Interaction Partners

The findings from Chapters 2 and 3 suggest that employees' depressive symptoms within organizations can be identified through observations of their interactions with surrounding employees. This identifiability involving surrounding employees is particularly evident among individuals who frequently interact with each other. Specifically, in Chapter 2, the correlation with depressive symptoms was stronger in *Clustering $w(B)$* , which weights interaction density when an employee's frequently interacting partners are interconnected. In Chapter 3, the significant correlation between physical engagement and partners' depressive symptoms remained robust even when limiting the analysis to only a small number of primary interaction partners (significant from two partners).

These findings explain the structural and behavioral characteristics of interactions related to depression in organizations, particularly among individuals who interact frequently. Studies show that social support from colleagues and supervisors serves as a social resource for employees, directly and indirectly influencing workplace stress and depressive symptoms (Johnson & Hall, 1988; Park et al., 2004; Dollard et al., 2007). Furthermore, studies using wearable devices have confirmed that face-to-face interactions during informal periods, such as break times, can be associated with organizational productivity (Waber et al., 2010; Watanabe et al., 2013, 2014), with one study specifically demonstrating that physical activeness during these break periods correlated with daily organizational performance (Watanabe et al., 2014), highlighting the role of physically active face-to-face interactions. Research has also indicated that exchanges between energized employees can enhance work motivation capability (R. L. Cross & Parker, 2004; Owens et al., 2016), and also the ability to cope with stress (Braha & Karabulut,

2024). These studies support the findings of this study that dense interaction and physical engagement among frequently interacting colleagues can be related to depressive symptoms as psychosocial factors affecting surrounding employees.

However, each findings focus on capturing features associated with individual depressive symptoms or those of surrounding individuals and do not provide a framework for an integrated interpretation of structural and behavioral characteristics. These two types of associations can be linked to depressive symptoms either separately or together. To comprehensively investigate the relationships between structural and behavioral influences, further analysis is needed to consider the contexts in which each factor becomes significant. For example, if density relates to belongingness and interactions with partners within such dense structures represent an important factor, then physical engagement observed in interactions within and outside such structures can provide additional contextual information.

While such analysis needs to be systematically investigated within complex network structures, the results partially confirm the possibility of observing these structural and behavioral characteristics together. Since key interaction partners are defined as individuals who share significant interactions with people around them, their depressive symptoms have a relatively dominant influence on their surroundings. This positional characteristic can contribute to the observation of a significant negative correlation between their depressive symptoms and the physical engagement of people around them (Fig. 3.5c). These analytical results from such a specific position suggest the possibility that one's depressive symptoms can be also observed through the behavioral characteristics of surrounding people.

In organizational settings, key interaction partners who are frequently chosen as primary interaction partners by other employees can be associated with leadership positions. Indeed, these key interaction partners were observed to be central employees actively

interacting with other employees within dense face-to-face interaction group structures, likely representing departments or social groups, in the visualized interaction network structures (Appendix F). Studies have consistently emphasized the significance of leaders' roles in organizational influence (Hsee et al., 1990; Kensbock et al., 2022; Sy et al., 2005). Leaders' positive moods have been shown to correlate with positive emotions and atmosphere among team members (Sy et al., 2005). Their mental health strongly affects the overall mental health of organization members (Kensbock et al., 2022), and they are also susceptible to members' emotions (Hsee et al., 1990). These findings support that the observed negative correlation between physical engagement in interactions centered on key interaction partners and depressive symptoms can be related to workplace emotional dynamics typically observed around leaders.

4.3. Interplay between Depressive Symptoms and Interactions within Organizations

The findings of this study have important implications for understanding the interplay between depressive symptoms and face-to-face interactions within organizations.

First, depressive symptoms can be structurally related to surrounding people. *Clustering*, which shows a negative correlation with depressive symptoms, is calculated as the ratio of actual triangular structures (where interactions also exist between two interaction partners) to the total possible number of triangular structures in one's interaction network as introduced in equation (3) of Section 2.2.5. However, this triangular structure is also included for the other people who belong to that structure. For example, when person i shares many common partners with person j , the number of triangles formed by i , j , and their common partners can be reflected in both i 's and j 's *Clustering* measures, potentially resulting in high *Clustering* values for both. These shared structural characteristics at the surrounding-level indicate that depressive symptoms among employees could also be a property that can be shared with their surrounding network.

Second, physical engagement was significantly associated with the depressive symptoms of interaction partners. People with severe depressive symptoms have been observed to show reduced physical expression and movement during interactions, which has been suggested to also affect their partner's physical movement and emotions (E. H. Bos et al., 2007; Girard et al., 2014; Joshi et al., 2013; Paz et al., 2022). The findings from Chapter 3 show that the relationship between physical engagement and depressive symptoms is prominently observed in interactions with interaction partners. This suggests that physical engagement can be characterized as an interactional process associated with partners' depressive symptoms in organizational settings. Two potential mechanisms underlying this interactional process, contagion processes and impaired interactions, were

discussed in Section 3.4. Specifically, in the contagion process, changes in physical engagement can precede the development of depressive symptoms. A pathway can be considered where physical engagement reduces in response to partners' depressive symptoms and this reduced physical engagement leads to a worsening of one's own depressive symptoms as the burden increases. This could explain why physical engagement is associated with partners' depressive symptoms (Fig. 3.3b) and, in key interaction partners who have high interactional influence within the organization, relates to their own depressive symptoms as well (Fig. 3.5a). In this case, reduced physical engagement serves as a preceding potential risk factor, suggesting that depressive symptoms can gradually converge among frequently interacting individuals. Alternatively, not actively engaging in interactions with depressed partners could be a result of impaired face-to-face interactions. From the perspective of physical engagement, impaired face-to-face interactions can lead to decreased positive effects such as the formation of relationships and smooth communication (Bernieri, 1988; Chartrand & Bargh, 1999) and increased negative effects of interactions such as stressful interpersonal events (E. H. Bos et al., 2007), while reducing emotional connection with interaction partners (Paz et al., 2022). Since these effects arise from the experience of impaired interactions themselves, rather than following partners' depressive symptoms as in contagion processes, they can manifest in various ways. For example, both individuals involved in the interaction can be affected, or in some cases, only one person experiences a significant impact. These effects do not necessarily lead to emotional similarity but rather reflect the distinct influence of the interaction on each individual. These potential mechanisms could operate independently, coexist, or be influenced by other external factors. Further investigation of these hypotheses will deepen the understanding of physical engagement in the context of interactions.

Together, the interaction characteristics identified as associated with depressive

symptoms in this study are partially shared among interacting employees or related to their depressive symptoms, suggesting that depressive symptoms in organizations are not confined to individuals but can be shared or influenced through interacting employees.

4.4. Limitations

Despite discussed possible interpretations and implications, the interpretations of the correlations in this study are limited in their causal interpretation, given that this is a cross-sectional study. The density of interactions and physical engagement can either influence the depressive symptoms of organization members, be influenced by them, occur simultaneously, or these relationships could be the result of other factors affecting each characteristic separately. In particular, interpretations warrant attention in cases where third variables can independently affect both depressive symptoms and interaction patterns. Nevertheless, the observations maintain valuable implication in such cases. The structural and behavioral characteristics observed in relation to depressive symptoms were identified through the interaction patterns of interaction partners. Therefore, even if third variables exist, they are more likely to be factors that affect the broader environment (e.g. team conflicts) rather than individuals specifically. This suggests that even if the observed interaction patterns originated from other factors, they can still be observed as characteristics of interaction patterns with surrounding employees. Furthermore, given the continuous influence of these interpersonal interactions among team members, they can function as critical indicators for understanding depressive symptoms within organizational environments.

The structural and physical interaction characteristics related to employees' depressive symptoms showed a significant negative correlation, but the coefficient was around -0.2, indicating a weak correlation. Thus, these correlations suggest limited relationships that require careful interpretation. However, given the complex nature of depressive symptoms, factors associated with CES-D generally show weak correlations, excluding direct components of depression (e.g., stress) (Oxman et al., 1992; O'Dougherty et al., 2012; Lin et al., 2020; Gutierrez et al., 2024). Therefore, the face-to-face interaction patterns

identified in this study also warrant investigation as potential factors related to depressive symptoms.

The dataset used in this study was anonymized to prevent identification of specific workplaces and individuals, and therefore does not include demographic information such as age and gender. These demographic factors are known to be potentially associated with depressive symptoms. For example, women generally show higher prevalence of depressive symptoms than men (Inaba et al., 2005; Sato et al., 2020). Moreover, demographic factors could influence different interaction patterns. For instance, workplace interaction patterns can vary across age groups and gender depending on the organizational context. Future research incorporating these demographic characteristics will be necessary for better interpretation of interactions related to depressive symptoms.

Although this study captures patterns related to depressive symptoms through objective measurement of interactions across various industries using a consistent methodology, both the sample size and scope of interpretation remain limited. Cultural context, in particular, warrants consideration. This study focused on ten corporate organizations in Japan. Japan, known as a high-context culture, tends to rely more on implicit communication (Hall, 1976). This cultural context can influence interaction patterns. For instance, the reliance on implicit communication amplifies the role of non-verbal communication in emotional exchanges (Kitayama & Ishii, 2002). Future research across more diverse cultural backgrounds, accounting for such cultural specificities, would contribute to a deeper and more robust understanding of interaction patterns associated with depressive symptoms in organizational settings.

Interpreting high CES-D scores directly as clinical depression is limited, as diagnosing clinical depression requires skilled professionals to evaluate the severity of each symptom, relationships between symptoms, and their persistence (Borsboom & Cramer, 2013; Borsboom, 2017). However, the CES-D offers several advantages for measuring

depressive symptoms as depression risk in workplace settings. First, as it was designed for the general population, its items are easy to understand and answer, requiring only about 5 minutes to complete. Additionally, its wide spectrum of scores (0-60) makes it useful for correlation analyses with related factors. Furthermore, it demonstrates high accuracy as a depression screening tool, effectively quantifying symptom severity as depression risk. For these reasons, the CES-D has been widely used to investigate depression-related factors in the general population (Oxman et al., 1992; O'Dougherty et al., 2012; Lin et al., 2020; Gutierrez et al., 2024).

5. Conclusions and Future Works

5.1. Conclusions

Depressive symptoms in the workplace are a critical issue concerning employees' mental and physical health, as well as productivity, and interactions among employees are significantly associated with depressive symptoms in relation to psychosocial factors. This study identifies interaction patterns related to employees' depressive symptoms using sociometric wearable devices that can objectively and comprehensively measure face-to-face interactions among employees. Considering that interaction patterns related to depressive symptoms can influence among employees beyond the individual level, two analyses were conducted examining comprehensively measured interactions among employees.

First, the analysis investigated structural characteristics at individual, surrounding, and organizational levels in social networks constructed from face-to-face interactions, and identified that higher density of interactions among employees with whom an individual interacts is associated with lower depressive symptoms. Furthermore, the density of structures surrounding an employee showed stronger associations with depressive symptoms when the employee had more frequent interactions with these interconnected colleagues, which also confirmed the importance of the direct face-to-face interaction.

Second, the analysis examined physical engagement, which refers to increased body rhythms during face-to-face interactions, and investigated the relationship between physical engagement and depressive symptoms in both the individual and their interaction partners. The analysis identified that employees' reduced physical engagement is associated with high depressive symptoms in their interaction partners. Analysis of primary interaction partners based on interaction frequency revealed that the correlation between physical engagement and depressive symptoms was observed even between just

two primary interaction partners. Particularly in interactions centered around key interaction partners who serve as primary interaction partners to multiple employees within organization, significant negative correlations were confirmed across all combinations of physical engagement and depressive symptoms between these key individuals and their surrounding employees. These findings suggest both the robustness of the correlation between physical engagement and depressive symptoms and the importance of interaction patterns with primary interaction partners.

Comprehensive analysis of organizational interactions through wearable devices revealed that employees' depressive symptoms are observable through their interactions with other employees. Specifically, lower depressive symptoms of an employee were observed through the dense connectivity among employees interacting with that employee, and the level of physical engagement during face-to-face interactions was associated with lower depressive symptoms of their interaction partners. In terms of structural characteristics, the connection density among frequently interacting employees was particularly important, suggesting that direct face-to-face interactions within the structure can be a positive factor for low depressive symptoms. Similarly, employees' high physical engagement was associated with lower depressive symptoms of their frequent interaction partners, indicating that factors related to depressive symptoms can be observed and influenced through direct interactions between employees.

In conclusion, depressive symptoms in organizations are observable through interactions between employees. Specifically, dense interaction structures and physical engagement among employees are associated with lower levels of depressive symptoms among them and their surrounding colleagues. These findings highlight the importance of examining structural density and physical engagement aspects when observing depressive symptoms related to organizational interactions.

5.2. Future Works

Future research could investigate the causality of these relationships. This study discussed various mechanisms that could explain the correlations between structural and physical face-to-face interaction patterns and depressive symptoms. For example, the structural density of face-to-face interactions can affect depressive symptoms through the formation of sense of belonging (Cockshaw et al., 2013, 2014), and physical engagement during face-to-face interactions can influence depressive symptoms through the transmission of vitality (Owens et al., 2016). Conversely, depressive symptoms can affect surrounding colleagues through the contagion of depressive emotions (Sy et al., 2005; Kensbock et al., 2022), potentially leading to reduced interaction density. Additionally, depressive symptoms can influence others through emotional and physical synchronization processes during interactions (Paz et al., 2022). These potential mechanisms could be examined through longitudinal studies and mediation analyses. For example, if structural density of interactions influences depressive symptoms, high structural density would be associated with decreased depressive symptoms in subsequent observations. Similarly, surveys including sense of belonging (Cockshaw et al., 2013, 2014), which could mediate between structural density and depressive symptoms, would provide more detailed interpretations about causal pathways.

Future research could explore the integration of structural and physical interaction patterns. In this study, while both structural and physical interaction patterns showed significant negative correlations with depressive symptoms, they were not integrated, as structural patterns were associated with employees' own depressive symptoms while physical patterns were associated with their partners' depressive symptoms. These patterns may capture different aspects of the same phenomenon, suggesting that their integration could potentially reveal stronger associations. Interestingly, these characteristics were

evident in interactions with primary interaction partners, suggesting that interactions with specific partners could play a significant role in relation to depressive symptoms. For example, if frequent interactions within a specific group are an important factor for lower depressive symptoms, examining the level of physical engagement during interactions with them could be more meaningful in context. Future research could provide clearer interpretations regarding depressive symptoms by specifically identifying and integrating contexts where structural and physical interaction patterns become significant.

A more detailed examination of key interaction partners is warranted for future research. Through the visualization of face-to-face interaction networks (Appendix F), key interaction partners were found to occupy central positions in modular interaction group structures, with their interactionally significant roles suggesting functions such as managers or mood makers. However, the current definition of key interaction partners cannot distinguish between those who are primary interaction partners to each other and those who are primary interaction partners to peripheral employees, potentially indicating qualitatively different roles depending on network structure. Additionally, the importance of key interaction partners is currently judged by the number of times they are selected as primary interaction partners in the entire organization, thus not considering structural characteristics at intermediate scales such as interaction group structures. Future research should incorporate organizational interaction structures to better identify and evaluate the significance of key individuals in workplace networks.

More detailed contextual situations of physical engagement could also be estimated. Recent neural network-based classification models have demonstrated that a relatively simple combination of accelerometer and gyroscope sensors can classify activities such as walking, sitting, running, and stair climbing with high accuracy (D. Zhang et al., 2022). Moreover, utilizing multiple sensors positioned on the chest, wrist, and ankle enables the classification of more complex behavioral patterns, including standing still, sitting and

relaxing, and frontal elevation of arms (Uddin, 2019). Implementation of such classification methods would contribute to a more detailed analysis of the relationship between physical engagement during face-to-face interactions and depressive symptoms, enabling better contextual understanding.

The observation of verbal signals can also be an important approach in relation to the qualitative aspects of interaction processes. The interplay between verbal and nonverbal communication has been recognized as playing a crucial role in how people interact with one another. Research has shown that when conveying emotions or attitudes, voice tone and facial expressions have a significant impact in cases where verbal content is neutral (Mehrabian & Ferris, 1967). Furthermore, comprehension is enhanced when speech and gestures align, while cognitive load increases and processing accuracy decreases when they are misaligned (Kelly et al., 2010). This interaction between verbal and non-verbal signals can provide qualitative insights into how emotions and information are conveyed during face-to-face interactions, with verbal signals playing a crucial role as carriers of information themselves. For example, even with active physical engagement, the quality of interaction can vary depending on the verbal contents. While collecting direct content of verbal interaction in workplace settings may be challenging due to privacy concerns, identifying meaningful qualitative aspects without violating privacy will be an important challenge. Information related to verbal interaction characteristics, including frequency, volume, pitch, and turn-taking patterns, could be leveraged for analysis (Ito-Masui et al., 2021).

The significance of surrounding individuals in interaction patterns related to depressive symptoms, particularly those with high interaction frequency, suggests potential applications for implementing cost-effective measurement and intervention strategies. Instead of continuously monitoring the entire organizational network to track depressive symptoms and interaction patterns, future research could implement targeted observations

and interventions focusing on interaction density and physical engagement within frequently interacting teams. Team-level observations enable consideration of specific contextual factors such as high workload periods or challenging phases. In terms of intervention, specific approaches could include sharing break times or modifying meeting and space arrangements to influence interaction patterns. For instance, when intervention is implemented at an organizational level, there has been a report that introducing open spaces to promote collaboration between employees actually resulted in decreased face-to-face interactions (Bernstein & Turban, 2018). Focusing measurements and interventions on frequently interacting groups could represent a more feasible approach and could provide more detailed insights into how psychosocial factors, through interactions, influence depressive symptoms within organizational settings.

Regarding interventions, specific attempts can be made from an interaction perspective. In organizations, people who are important for social interactions, such as mood-makers who enjoy interacting with others, are often understood as having innate qualities. Instead, interventions and training have primarily focused on managers who need to coordinate work and make decisions while interacting with various organizational members (Evans-Lacko & Knapp, 2018; Gayed et al., 2018). Meanwhile, high-quality interactions that generate and share vitality exist not only with supervisors but also among colleagues and team members (Owens et al., 2016). Therefore, in addition to training managers, interventions can be implemented focusing on positive interaction patterns to address depressive symptoms. For example, the key interaction partners identified in this study who held important positions in structural and physical interaction patterns were closely associated with depressive symptoms among those around them. While artificially developing or intervening with such individuals may be quite challenging, it can be possible to create opportunities for such individuals to be active with positive mood, for example, through break times or workshops. Alternatively, interventions using robots or

applications could be explored. Studies are examining how the appearance and interaction features of robot coaches influence their effectiveness in promoting employee mental health (Spitale et al., 2023), while the impact of applications designed to facilitate employee interactions is also being investigated regarding the physical movements related to depressive symptoms of team members (Tsuji et al., 2024). In these intervention attempts, physical engagement and structural density could be examined for their potential positive effects in relation to employees' depressive symptoms.

Additionally, it would be valuable to examine the effects of demographic information (e.g., age and sex), individual differences such as specific personality traits (e.g., extraversion, neuroticism) and physiological factors (e.g., cortisol levels), and contextual workplace information such as job positions and types of industry. For example, individuals high in extraversion tend to be more expressive and responsive to positive emotions, while those with high neuroticism show stronger reactions to negative emotions and display less consistent emotional expression (Jensen, 2016; Larsen & Ketelaar, 1991; Riggio & Riggio, 2002). These personality traits could shape how people interact with others and process their emotions. Information about job positions in the workplace could also be significant. For instance, those in higher positions can have more opportunities for face-to-face interactions with a wider range of people. Relationships with immediate supervisors are not only related to employees' job engagement and productivity (Owens et al., 2016), but also have stronger impacts on negative factors such as bullying (Colligan & Higgins, 2006). These positional characteristics can be connected to the characteristics observed among those classified as key interaction partners who are distinguished by their significant interactional influence on other employees within the organization. Additionally, this study focused on office workers as they were suitable subjects for comprehensive observation of face-to-face interactions within organizations through sociometric wearable devices. The findings limited to office workers may capture patterns

of face-to-face interactions specific to sedentary work environments, such as settings where physical and social activity are typically restricted. The role and significance of face-to-face interactions can vary across different environments, and their patterns and importance related to depressive symptoms can differ by environment. Further validation is needed in occupational settings that involve more diverse physical and social activities. Analysis incorporating the diverse information discussed above would enhance the understanding of the specificity and universality of the interaction patterns in relation to depression within workplace.

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Research Achievements

■ Publications Related to This Thesis

- Peer-reviewed Journal Papers

1. Lee, J. H., Sato, N., Yano, K., & Miyake, Y. (2022). Universal association between depressive symptoms and social-network structures in the workplace. *Scientific reports*, 12(1), 10170.
2. Lee, J. H., Sato, N., Ogata, T., Yano, K., & Miyake, Y. (2024). Physical Engagement in Face-to-Face Interaction Is Associated with Depressive Symptoms of Interaction Partners in the Workplace. *Behavioral Sciences*, 14(11), 1006.

■ Publications Not Directly Related to This Thesis

- Peer-reviewed Journal Papers

1. Lee, J. H., & Ogawa, K. (2023). Emergence of a mutual-growth mechanism in networks evolved by social preference based on indirect utility. *Scientific Reports*, 13(1), 21680.

Appendix

Appendix A. The criterion for empty intervals between interactions

The weight of the relationship is quantified as the number of interactions. However, examination of the interactions (Fig. S1a) showed that short empty intervals frequently appeared between the interactions (Fig. S1b). These empty intervals can be caused by misalignment between the infrared sensors of the wearable sensors, or can actually be caused by intermittent interaction. Based on the characteristics of these intervals, it is more reasonable to regard the interactions that occurred over such a short interval as a continuous interaction rather than interactions in a completely new context. The interval less than 5 minutes was set as the criterion for imputation, which is not a long time perceptually, and appears with a high frequency in the data. This criterion allows for a more reasonable counting of interaction frequency (Fig. S1a), and further analysis confirmed that the results, the correlation between depressive symptoms and *Clustering*, *Clustering* $w(B)$, are robust regardless of the specific threshold of ‘5 minutes’ (Fig. S1c).’

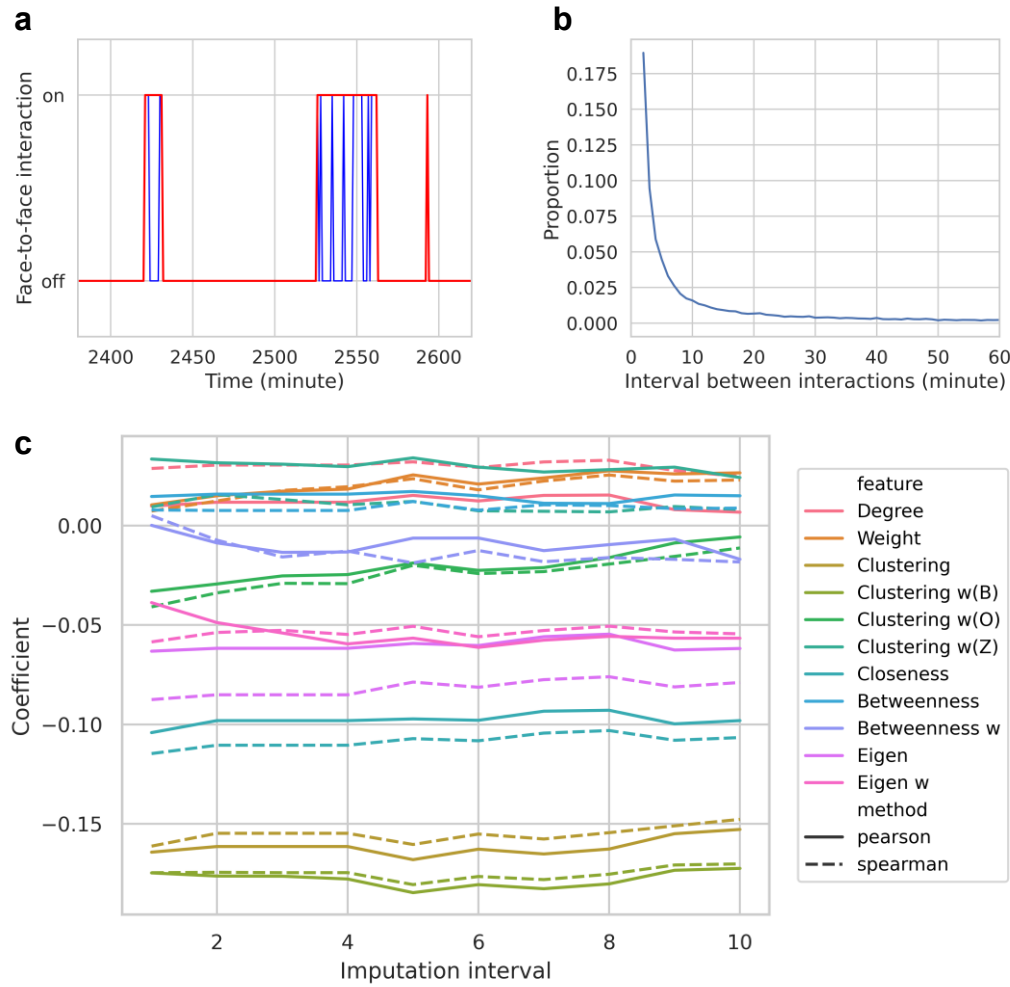


Figure S1 Imputation of face-to-face interaction data. a) The observed face-to-face interactions between two specific people over a period of about 4 hours. The blue line represents the observed interaction, and the red line represents the corrected interaction. b) The proportion distribution of intervals between interactions. It can be seen that short intervals appear with high frequency. c) Changes in correlation between depressive symptoms and social network characteristics according to the threshold of the interval used for imputation. It shows that the correlations are robust regardless of the threshold.

Appendix B. The criterion for baseline window spans

In this study, the baseline body rhythm was defined as the average body rhythm during the 30 min preceding an interaction, referred to as the baseline window span. To evaluate the potential impact of this methodological choice on the results, additional analysis investigated how varying the baseline window span from 10 to 60 minutes affected the findings.

The correlations between physical engagement and depression scores were examined across different baseline window spans (Fig. S2). The main findings remained statistically significant ($p < 0.001$) across the range of baseline windows from 10 to 60 minutes: The correlation between physical engagement and depression score (partner), and the correlation between physical engagement (partner) and depression score (partner).

This consistency demonstrates the robustness of the main findings, indicating that they are not artifacts of the specific choice of a 30 min baseline window span.

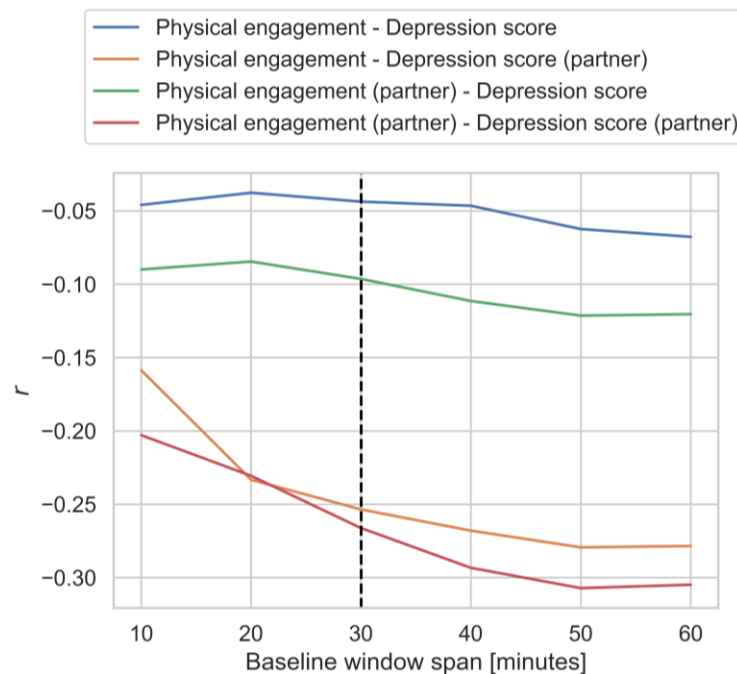


Figure S2 Correlations between physical engagement and depression scores of employees and their partners based on different baseline window spans. The black dashed line represents the 30-minute baseline window span established in this study.

Appendix C. Body rhythm before and after face-to-face interaction logs

To more accurately define the body rhythm increase induced by face-to-face interactions, the average changes in body rhythm were examined before and after face-to-face interactions (Fig. S3a, b). The results show that the impact of face-to-face interactions on body rhythm extends approximately 10 minutes before and after the interaction. These effects can include misalignment between wearable devices, physical activities due to mutual recognition (such as greetings), and contexts like movement or preparation before interactions. In particular, as identified in the data preprocessing procedure, the misalignment issue could affect the precise detection of the exact starting point of face-to-face interactions. Therefore, the analysis determined that the interaction's influence exists within a broader window where its effects on body rhythm are confirmed.

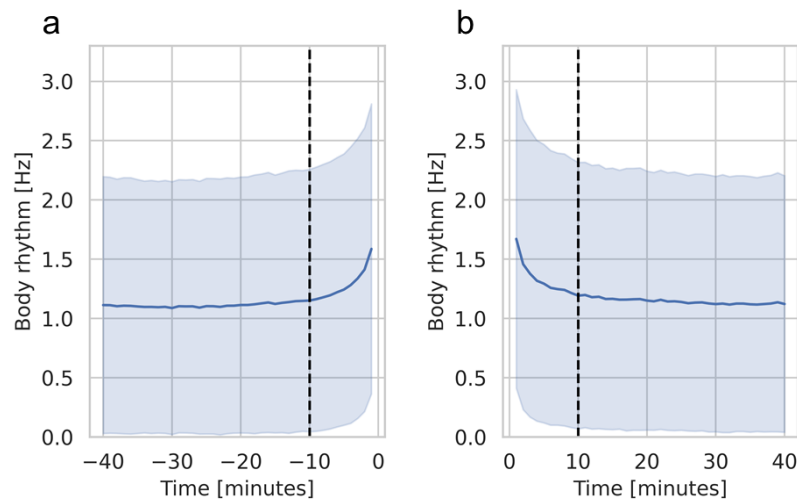


Figure S3 Body rhythm before (a) and after (b) face-to-face interaction logs. For all observed body rhythms before and after face-to-face interaction logs, solid lines represent mean values, and shaded areas indicate standard deviations. Dashed lines in (a) and (b) denote the time points that are 10 minutes before and after the interaction, respectively.

**Appendix D. Distribution of increased body rhythm (physical engagement)
during face-to-face interactions compared to baseline**

Figure S4 provides visual representations of the distribution of increased body rhythm during face-to-face interactions compared to baseline, which is defined as physical engagement.

Figure S4a shows a histogram of the data, displaying an approximately bell-shaped distribution consistent with the reported mean (0.26) and median (0.24). The near-symmetry of the distribution is visually evident, aligning with the reported skewness (0.00896).

Figure S4b presents a Q-Q plot, comparing sample quantiles with theoretical quantiles from a normal distribution. The plot demonstrates a strong linear relationship, particularly in the central region, suggesting a close approximation to normality. Slight deviations at the extremes suggest marginally thicker tails, consistent with the reported kurtosis (0.97).

Together, these visualizations corroborate the numerical summary statistics and support the assumption that the distribution of body rhythm increase sufficiently approximates normality.

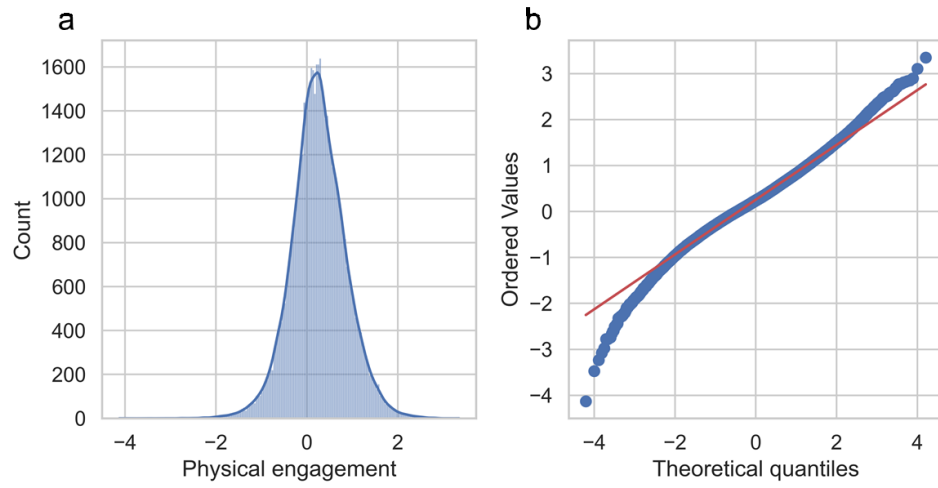


Figure S4 Distribution of increased body rhythm (physical engagement) during face-to-face interactions compared to baseline (a), and Q-Q plot comparing the sample quantiles of increased body rhythm to the theoretical quantiles of a normal distribution (b).

Appendix E. Spearman correlation analyses to examine the association between physical engagement and depression scores.

To verify the robustness of the primary results in Section 3.3 against outliers or non-linearity, Spearman's correlation analyses was conducted to examine the association between physical engagement and depression scores among employees and their face-to-face interaction partners.

1. The correlation between physical engagement and depression score:

$$r_s = -0.04, p = 0.424$$

2. The correlation between physical engagement and depression score (partner):

$$r_s = -0.26, p < 0.001$$

3. The correlation between physical engagement (partner) and depression score:

$$r_s = -0.08, p = 0.082$$

4. The correlation between physical engagement (partner) and depression score (partner) :

$$r_s = -0.25, p < 0.001$$

Spearman's correlation analyses demonstrated significant results in two primary associations consistently observed across Sections 3.3.1, 3.3.2, and 3.3.3: (1) the correlation between physical engagement and depression score (partner), and (2) the correlation between physical engagement (partner) and depression score (partner). These consistent findings demonstrate that the main results are robust to outliers and potential non-linear relationships.

Appendix F. Face-to-face interaction networks and key interaction partners.

Figure S5 shows face-to-face interaction networks of 10 organizations and the positions of key interaction partners. Key interaction partners are displayed in larger sizes to distinguish them from other nodes. Group structures observed in the interaction networks were visualized using the Louvain algorithm to assess the positions of key interaction partners relative to potential departments or social groups. Visual inspection revealed that key interaction partners were located at the center of groups with active interactions, rather than at bridge positions connecting different groups. This is related to the characteristics of group structures observed in face-to-face interaction networks. Since group structures have high internal interaction frequency, central employees within a group are more likely to be primary interaction partners for other employees. In other words, the definition of key interaction partners is related to identifying central people within interaction groups such as departments or social groups.

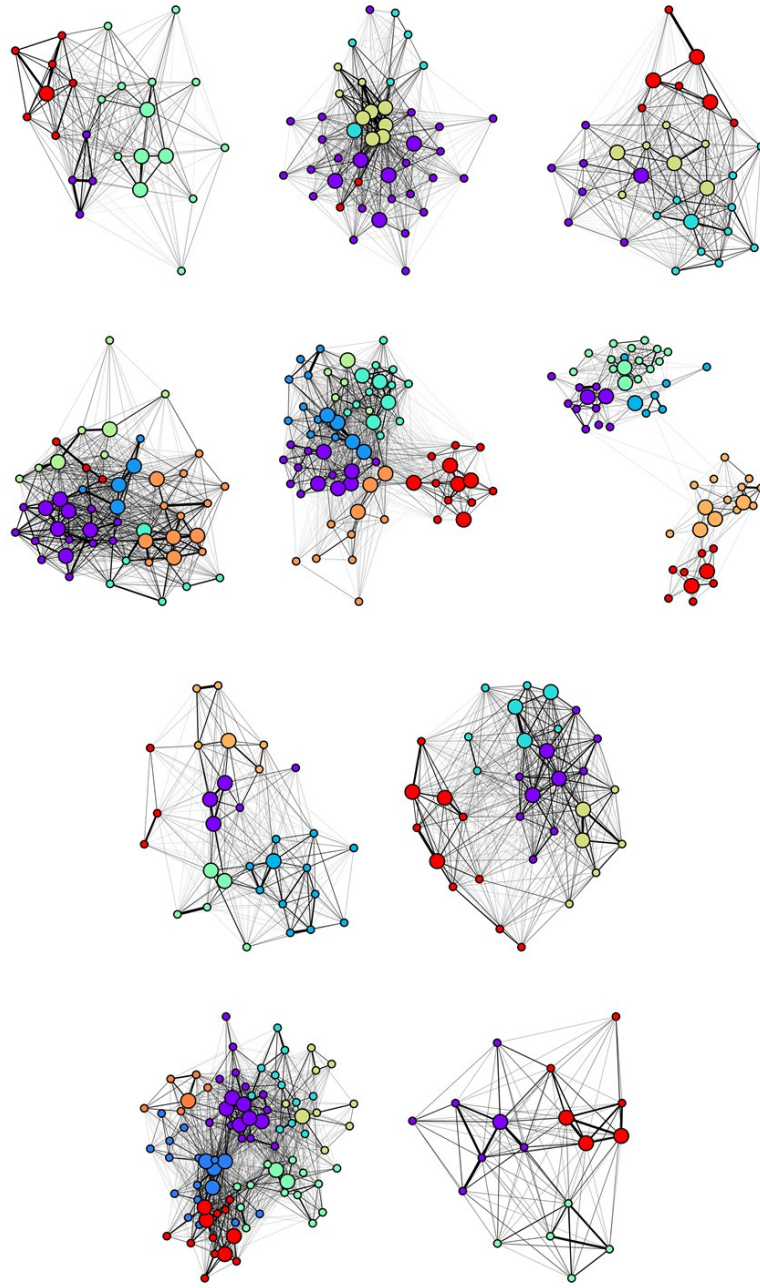


Figure S5 Face-to-face interaction networks and key interaction partners. Larger nodes represent key interaction partners. Group structures are visualized using communities detection via the Louvain algorithm (Blondel et al., 2008), and nodes of same color indicate membership in the same group. The width of the links is proportional to the daily average frequency of face-to-face interactions. Visualization was created using Python's NetworkX package (Hagberg et al., 2008), with node positioning determined by the Fruchterman-Reingold force-directed algorithm applying spring forces to links, resulting in nodes with frequent interactions clustering together and central nodes gravitating toward the center of the layout.