Multilevel empirical research

A call for more mixed-methods approaches

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Multilevel empirical research: A call for more mixed-methods approaches

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Abstract

Organizations are complex multilevel social systems, in which individual members frequently execute diverse tasks within their functional units or teams to advance strategic goals over a period of time. Diverse organizational phenomena are, therefore, inherently shaped by factors from different levels and can be comprehensively studied by embracing multilevel research designs. In this introductory paper, we review different multilevel approaches used in management and organization studies to contextualize four papers published as part of this management focus on multilevel research. We also discuss several directions for future research. We strongly advocate for scholars like you to conduct more multilevel qualitative and mixed-methods studies that can address complex business and societal challenges. The need for such research designs is urgent and important in our scholarly field, and your contribution can make a significant difference.

1. Introduction

Organizational phenomena are multilayered, complex, and messy (Chan, 1998; Humphrey & LeBreton, 2019: Kozlowski & Klein, 2000). Although this has been multidisciplinary acknowledged across management and organization studies (Hitt et al., 2007; Mathieu & Chen, 2011; Molloy et al., 2011), we still tend to debate about macro-, meso-, and micro-level organizational research as if our scholarship could, either conceptually or empirically, neatly fit only one level of theory and analysis (Hernaus et al., 2020). To illustrate, consider the widely studied construct of organizational culture, defined as "*a pattern of shared basic assumptions that was learned by a group as it solved its problems of external adaptation and internal integration, that has worked well enough to be considered valid and, therefore, to be taught to new members as the correct way to perceive, think, and feel in relation to those problems*" (Schein, 2010, p. 18). Organizational culture has been regularly conceptualized and theorized as a key organizational- or macro-level construct in disciplines such as organization theory and strategic management. However, this key organizational attribute emerges from teams or departments (i.e., meso-level). Moreover, it is primarily operationalized at the micro-level as individual (employee) perceptions and opinions of organizational assumptions and corporate values, thus creating incongruence between the levels of theory, measurement, and analysis (see Molina-Azorín et al., 2020).

The multilevel nature of organizational phenomena has a long and rich tradition in micro-level disciplines such as organizational psychology, organizational behavior, and human resource management. This tradition has been mainly driven by advances in multi-level statistical analyses (Preacher et al., 2010; Aguinis et al., 2011; Aguinis & Molina-Azorín, 2015). Organizational scholars from macro-level disciplines such as strategic management, organization theory, and international business likewise conduct multilevel research extensively. Despite the recent advances in multilevel theory, measurement, and

design (Humphrey & LeBreton, 2019; O'Connell et al., 2022), there are still many substantive areas within the organizational sciences lacking rigorous research – quantitative, qualitative, or mixed – that is needed for having nuanced theoretical explanations for our studied phenomena.

In our call for stronger, more robust integration of individual, team, organizational, and multilevel perspectives in organizational research (Hernaus et al., 2020, p. 217), we have outlined the need for more rigorous research that would advance *"our understanding of the multilevel nature of organizations."* We received a number of submissions. However, only four were aligned with our editorial mission and evaluated by reviewers as making rigorous and significant contributions to contemporary organizational research. In this introductory paper, we review the major multilevel models and frameworks that have driven quantitative and qualitative research. We then offer a brief discussion of how the multilevel nature of organizational phenomena can be theoretically explained. We conclude with several potential avenues for future research and offer an overview of the papers comprising this management focus.

2. Different multilevel models and frameworks

This section reviews influential and promising frameworks to conceptualize, operationalize, and analyze multilevel organizational phenomena. Multilevel research is present in both qualitative and quantitative literature. Although some frameworks have been used in both, a few specific models have been conceptualized exclusively for dealing with quantitative data, and some are appropriate for organizing and analyzing predominantly qualitative work. A reader should note that our synthesis is not exhaustive as we are unfamiliar with all disciplinary areas in organizational research and beyond. Instead, we provide an overview of critical frameworks that have been either exceptionally influential so

far or have shown great promise to drive future, innovative multilevel studies, such as the typology of composition models (Chan, 1998), social networks (Brass et al., 2004), system dynamics (Sterman, 2002), socio-ecological systems perspective (Bronfenbrenner, 1977), and proxemic law (Le Goff et al., 2022).

2.1 Typology of composition models

We start with Chan's (1998) typology of composition models, one of the most influential frameworks and a key driver of a large body of multilevel research in organizational psychology, human resource management, and organizational behavior. This typology outlines the nature of relationships between constructs or phenomena that are believed to originate at a lower-level (e.g., individual-level perceptions of the work environment), but actually emerge and are manifested at a higher-level (e.g., organizational climate, measured using organizational-level means of the individual-level perceptions). According to Chan (1998), five primary types of composition models can explain how concepts from a lower level emerge at a higher level and how the lower-level data should be aggregated or combined (see LeBreton et al., 2023) to represent a higher-level construct.

Additive models are so-named because the process of aggregating lower-level data involves computing a mean or sum of the lower-level data and using those means/sums as indicators for the higher-level construct (Chan, 1998). This model is consistent with Kozlowski and Klein (2000)'s *pooled unconstrained model of emergence.* The latter authors noted that elemental content (i.e., lower-level scores) may be very similar or vary dissimilar. Stated alternatively, the variability within higher-level units is irrelevant when using additive models to reflect pooled unconstrained models of emergence.

Direct consensus models also involve aggregating lower-level data by computing means or sums for each higher-level unit (e.g., organization), but this model places an

additional requirement on the data – there must be sufficient within-unit agreement or consensus in order to justify aggregating scores to a higher level (Chan, 1998). Similarly, the *referent-shift consensus model* also aggregates lower-level data using means or sums and also uses sufficient within-group agreement (consensus) as a criterion that must be met prior to data aggregation. These two models only differ in the referent used in the questions or items. In a direct consensus model, the individual typically serves as the referent (e.g., I believe I can perform the task) whereas with the referent-shift consensus model, the questions are now asking about a different referent or target (e.g., I believe my team can perform the task). Researchers adopting consensus models compute estimates of within-group agreement such as rWG, aWG, or AD (see LeBreton & Senter, 2008 for a review of commonly used measures of within-group agreement) to justify the aggregation of lower-level data (e.g., employee perceptions of work environment) to a higher-level (e.g., team or organizational level). Kozlowski and Klein (2000) noted that consensus composition models are typically used with *convergent emergence models* – basically, the higher-level construct only emerges (i.e., exists) once sufficient consensus or agreement has accumulated among the lower-level units.

Chan (1998)'s *dispersion model* is used when differences in the element content of the lower-level data are used to operationalize scores between higher-level units. Simply stated, the variation within-units is used to measure the scores on the higher-level construct. Dispersion composition models are most appropriate for reflecting *variance emergence* constructs (Kozlowski & Klein, 2000). Dispersion composition models involve computing a measure of within-group dissimilarity (e.g., standard deviation, variance, range, and coefficient of variation) as the indicator for the higher-level construct. For example, Schneider et al. (2002) used both a consensus model and a dispersion model to study how service climate was related to customer perceptions of quality. Specifically, they used a

consensus model to compute the level of service climate (i.e., averaged employee-level climate perceptions after establishing a minimal level of within-group agreement) and a dispersion model to compute the strength of service climate (i.e., within-bank standard deviation in employee-level climate perceptions).

Whereas Chan (1998)'s initial composition models all focused on static constructs (e.g., service climate and team efficacy), his *process model of composition* is appropriate when the focus of researchers is on understanding whether the basic processes connecting constructs at a lower-level are also appropriate for reflecting relationships between similar constructs at a higher level. Chan (1998) referenced work by Kozlowski et al. (1996) to illustrate how self-regulation processes (lower-level) could be conceptualized as having team-level (higher-level) analog denoted as team self-regulation.

It is important to note that the specific choice of composition model will depend on the research question and theory that the study aims to address and test. In other words, the researchers have to explain and theoretically justify how their studied phenomena may emerge at higher levels, which should then guide their method or choice of composition model. Thus, certain higher-level constructs require certain composition models, because those constructs follow certain patterns of emergence. We illustrate the composition models by drawing from the research on HR practices (see Figure 1), which has proliferated since the publication of an influential paper by Huselid (1995). The use of specific HR practices can be operationalized either in terms of HR managers' or CEOs' scores or by means of aggregating employee perceptions to the organizational level. Whereas the former measures HR practices using organizational-level data, the latter approach requires one of the composition models to aggregate the individual-level data to the organizational level.

If we were following an additive model, we would aggregate individual perceptions of HR practices to the organizational level without exploring the degree of agreement between

these perceptions. Such an approach could be justified to operationalize the designed HR practices or HR systems where homogeneity is assumed - also called the intended HR system (Boon et al., 2019). If we followed a direct consensus model, we would first check whether there is enough agreement between individual perceptions of HR practices in their organizations before aggregating these perceptions to the organizational level. This approach would be appropriate if the emergence of the organizational-level construct depended on within-organization consensus in individual perceptions of HR practices. Next, a referent-shift consensus model would require that the individual-level items of HR practices use a higher-level referent, for instance, "an organization", for the organizational-level study of HR practices. This approach maximizes the agreement between individual perceptions of HR practices by making individuals think of the organization as a whole rather than their own experiences (Boon et al., 2019). Once sufficient agreement between individual perceptions is established, we can proceed with aggregating them to the organizational level, which would conceptually represent collective perceptions of HR systems (Sanders et al., 2008).

We may also be interested in studying the agreement (or lack thereof) between individual perceptions of HR practices within an organization rather than their average level. Dispersion composition models could be applicable in this case, whereby the organizational-level HR practices would be operationalized by using variance between individual perceptions of HR practices in their organizations. Conceptually, the agreement between individuals in their perception of HR practices in their organizations refers to the HRM strength (Bowen & Ostroff, 2004). The higher the strength of HR practices, the more consistently the HR practices are implemented across the organization. Finally, we may be keen to explore how individuals reach agreement and shared understanding of the HR practices in their organizations (Ostroff & Bowen, 2016). To this end, we could follow process composition models and propose a model in which the parameters shaping individual

perceptions of HR practices are homologous to the parameters shaping shared perceptions of HR practices. Therefore, the choice of the composition models is based on what higher-level construct is conceptually relevant to the research questions.

Insert Figure 1 about here

The typology of composition models is inherently underpinned by assumptions of variance between lower-level scores and the summation or averaging of these scores to operationalize higher-level constructs. As such, it can only be applied in quantitative organizational research.

2.2 Social networks

Another approach to studying multilevel organizational phenomena involves exploring social networks (Brass & Borgatti, 2019; Brass et al., 2004; Newman & Wang, 2019; Paruchuri et al., 2019; Zappa & Lomi, 2015). Social network research focuses on actors who form part of interconnected social relationships. Actors could be individuals, teams, or organizations representing nodes within the network. The relationships between different nodes (i.e., actors) are called ties. Rather than focusing on actors' characteristics or attributes in isolation, the social network approach explores ties or lack of ties between different actors and how the characteristics of these ties shape different outcomes (Brass et al., 2004). The characteristics of social networks are often operationalized in terms of network size (i.e., number of direct and secondary ties), strength (i.e., the average strength of ties in the network; a tie strength can be operationalized as the number and reciprocity of relationships, the affective intensity of a relationship, or the duration of the relationship), brokerage (i.e., the extent to which actors bridge structural holes or disconnected parts of the network),

closure (i.e., the extent to which the actors in one's network are also related), and diversity (i.e., the extent to which actors in one's network are diverse in terms of functional and demographic characteristics) (Baer et al., 2015).

Organizational network research (see Borgatti & Foster, 2003; Chen et al., 2022) has studied these network characteristics as well as antecedents and consequences of networks at interpersonal (i.e., networks that explain relationships between individuals within a team or organization), inter-team (i.e., networks that describe how teams or work units interact within an organization), and inter-organizational levels (i.e., networks that explain the cooperation between different organizations). For instance, at the interpersonal level, several studies have looked at how the characteristics of interpersonal networks shape employee creativity and innovation (e.g., Anderson et al., 2014; Baer et al., 2015), with results showing that brokerage has the strongest positive direct relationship with individual actor's innovative behaviors. At the inter-team level, a considerable amount of research has looked at how teams within the same network share information. A study by Mell et al. (2020) has found that teams with members who identified predominantly with their network as a whole (i.e., system-focused teams) shared information with all teams in their network equally. However, teams whose members identified with their respective teams (i.e., team-focused teams) shared less information with system-focused teams compared to other team-focused teams in their networks. At the inter-organizational level, several studies have looked at inter-organizational learning. For instance, an insightful study by Gibb et al. (2017) has differentiated between organizational learning episodes of how to compete and perform and showed how small organizations in the same industry learned about tackling common problems that led to strategic goals-setting and ultimately cooperating in fulfilling these goals.

The above examples show how organizational research tends to analyze networks at different levels of analysis. Surprisingly, there has been little research on social networks

combining multiple analysis levels within the same study. Based on the research evidence, it would be conceivable to expect that the characteristics of interpersonal ties (e.g., network size) are a function of inter-team ties and their characteristics (e.g., charismatic team leaders who connect different teams), which in turn are shaped by the characteristics of the industry in which their organizations form networks with their competitors (e.g., sourcing top candidates from a limited pool). Zappa and Lomi (2015) have offered an analytical procedure that can be used to study the mechanisms that explain the inter-relationships between individuals in organizations – the analysis called multilevel exponential random graph models (MERGMs). As noted in their paper, "*while alternative statistical models exist for studying organizational social networks, MERGMs are the only existing models that allow direct modeling of interdependences induced by known relational mechanisms. Common examples of such mechanisms include reciprocity (the tendency of individuals to prefer social relations characterized by mutuality) and transitivity (the tendency of individuals sharing partners to become directly connected)*" (Zappa & Lomi, 2015, p. 543). We would like to encourage future research to employ such modelling to study complex network dynamics across multiple levels of analysis (see Figure 2 for an example).

Insert Figure 2 about here

Social networks approach is sometimes used to analyze dyadic data because networks may be conceptualized as a series of dyadic connections between individuals (see Kenny et al., 2006). However, dyadic data does not always necessitate the use of social network analyses – this will depend on one's research question. Nevertheless, many dyadic scenarios will require a multilevel approach (Knight & Humphrey, 2019; Krasikova & LeBreton, 2012; Tse & Ashkanasy, 2015). Dyads or dyadic relationships conceptually represent the interactions between two actors at lower levels of analysis (e.g., most often individuals) who

are nested within a higher level (e.g., a dyad) and, as such, require a multilevel approach to theory development, operationalization, and analyses (Knight & Humphrey, 2019; Krasikova & LeBreton, 2019). Conceptually, dyadic relationships involve mutually interdependent actors who have a common goal, and as such, they work together to achieve this common goal, and they adapt their behavior, if necessary, to maintain their mutual relationship (Krasikova & LeBreton, 2012; Tse & Ashkanasy, 2015). Such dyadic-level data can be analyzed using the actor–partner interdependence model (i.e., a model to study dyadic relationships between individuals who form a single dyad; for instance, an employee [actor] and his or her spouse [partner] in work-life balance research), the one-with-many model (i.e., a model to study dyadic relationships that an individual actor forms with multiple "partners" within a team or organization; for instance, a leader with different followers in LMX research), and the social relations model (i.e., a model to study dyadic relationships between individuals who form the same team; for instance, team members' satisfaction with each other's work in team research), or using network analysis (Kenny et al., 2006; Krasikova & LeBreton, 2012). Even though the research on social networks has mainly been quantitative, the social network analysis can also be underpinned by qualitative data (e.g., Gibb et al., 2017; Kim & Maltseva, 2023), thus leading towards qualitative social network analysis' insights.

2.3 System dynamics approach

Up to this point, we have discussed how the multilevel paradigm is well-suited to advancing research involving largely static constructs, and static relationships span hierarchically-nested data structures (e.g., employees nested in teams nested in organizations). However, this paradigm is also well-suited to data that are temporally nested (e.g., repeated measures nested within employees). Although early work tended to focus on

methods used to document and predict patterns of growth and decline (Bliese & Ployhart, 2002; Ployhart & Hakel, 1998; Raudenbush & Bryk, 2002), more recent research has sought to further expand the multilevel paradigm to better incorporate concepts related to adaptation, complexity, and dynamics (see Aiken et al., 2019; Cronin & Vancouver, 2019).

One especially promising interdisciplinary approach to address these ideas is called *system dynamics*, which can be used to analyze the behavior of complex systems across different disciplines, including management, engineering, medicine, economics, environmental studies, public policy, and other social sciences (Sterman, 2000). System dynamics is underpinned by the theory of non-linear dynamics and feedback control that comes from physics, mathematics, and engineering, as well as organization theory, social and cognitive psychology, and other social sciences to provide a foundation for understanding and modeling complex human and technical systems (Sterman, 2002). One key characteristic of the system dynamics approach is its ability to capture and explore complex, multilevel dynamic phenomena over time. For instance, it helps us determine appropriate policy interventions (e.g., Zhu et al., 2021) and public sector innovations (e.g., Jadeja, 2022), as well as evaluate the long-term consequences of complex decisions (e.g., Brailsford et al., 2014).

System dynamics considers systems as sets of interacting elements that influence and are influenced by each other over time. Dynamic complexity is one of the features of this approach, resulting from the interactions between elements or agents in the system over time. This makes dynamic systems tightly coupled, constantly changing, determined by feedback, nonlinear, self-organizing, and adaptive, amongst other characteristics (Sterman, 2002). The issue of feedback and feedback loops is fundamental to system dynamics as it outlines that systems react to our actions and decisions, leading to changes in our environment, which in turn lead to new actions and decisions. Another critical feature of system dynamics is stocks and flows, which are depicted as rectangles and arrows (see Figure 3). A stock (i.e., a

rectangle) represents the accumulation in the system, whereas a flow (i.e., an arrow) refers to the rate of change between stocks or within a stock over time; an in-flow replenishes the stock, and the out-flow drains it (Sterman, 2002).

Insert Figure 3 about here

System dynamics modeling typically uses simulations to study complex models integrating dynamics, interactions, feedback loops, and nonlinear effects (Van Oorschot et al., 2010). The ability of the system dynamics approach is relevant to multilevel research if we tend to model the system's elements and interactions between them across multiple levels of analysis. For instance, the system dynamics modeling could be used to study the interrelationships between institutional- (e.g., government policy), market- (e.g., market demands), organizational- (e.g., organizational support and slack resources), team- (e.g., team collaboration), and individual-(e.g., employee knowledge, skills, and abilities) level factors and how all these factors shape new product development (e.g., see Li et al. [2021] for a similar system dynamics model studying multilevel motivations towards green design practices).

2.4 Socio-ecological systems perspective

Most multilevel organizational research implies that the broader context shapes individual, team, and organizational phenomena. The socio-ecological systems perspective has been a valuable framework for studying organizational phenomena that are impacted by factors stemming from broader environmental factors spanning multiple levels. Initially developed as a model of human development (Bronfenbrenner, 1977), the socio-ecological systems theory argues that individuals are nested within multiple interactive social systems

that emerge at multiple levels. Social systems represent collective units composed of interdependent and interactive individuals who share common goals and the same environment, such as families, teams, organizations, communities, and countries (Fan et al., 2021). Different social systems are interconnected and related; for instance, an individual is a part of the family and his or her school, university, or organization. Therefore, individual experiences in multiple domains, including work, are inherently shaped by the interactions across these multiple social systems.

Bronfenbrenner (1977) suggests that five different systems affect individuals. Microsystems are those with which individuals directly interact, such as family members, work colleagues, or line managers. Mesosystems, in turn, represent interactions between multiple microsystems. For instance, an individual is affected by both family and work environments when working from home. Further, exosystems, such as neighborhoods and organizational departments, influence individuals indirectly. Macrosystems refer to broader cultural, social, and legislative contexts, such as employment law or saving face as a cultural norm, which will shape individual behavior. Finally, chronosystems capture the pattern of life transitions over time by paying attention to career trajectories and how changes in one's career might influence their behavior. In essence, the socio-ecological systems perspective suggests that individuals will interact with these five environmental systems over their life course (see Figure 4 for an example of the socio-ecological systems perspective to study individual creativity).

Insert Figure 4 about here

In organizational research, the socio-ecological systems theory has been used to study diverse topics such as workplace diversity (e.g., Bond & Pyle, 1998), gender inequality in STEM (e.g., Michell et al., 2018), and work-life balance (e.g., Fan et al., 2021). Although

most of these studies have used qualitative or mixed-methods research designs, the socio-ecological systems theory could also be applied to quantitative studies, for instance, by exploring cross-level interactions between factors from macrosystems or exosystems and their effects on individual microsystem experiences.

2.5 Proxemic law

Proxemic law is a nascent approach in management and organization studies that has been mobilized to study the role of context in complex multilevel phenomena (Le Goff et al., 2022). The core idea of this approach rests on the premise that individual actors, such as employees, are embedded within a particular space, such as their organization or workplace, and they develop a subjective representation of this space, appropriate it, and move within it. In this sense, each actor has their interpretation of the environment or context in which they work. According to the proxemic law, the individual actors would be influenced more by events, people, objects, etc., closer to them (rather than further away) in this subjective space (Robert et al., 2023). Once the value of the most proximal factors has been exhausted, for instance, when the factors in their most proximal space do not significantly improve actors' performance, the actors would move further away to search for other events, people, objects, etc., that can help them perform better (see Figure 5).

This approach draws from two other ideas to show how an individual actor may appropriate and move within their space. One idea is that of a "wall", which can direct an actor's movements within their space in a particular direction. The walls are socially constructed and perceived as anything that stops or interrupts the actors' movements in their space, such as red tape, legislation, rules and procedures, etc. These walls can be perceived as more or less thick, and the actors can cross them, in which case they will create "doors" that

can also be used by other actors. All walls are permeable, but some are so thick that the actors may be dissuaded from crossing them (Le Goff et al., 2022).

Insert Figure 5 about here

This novel and promising approach to studying how organizational context may shape employee behavior uses an inductive research design. Le Goff et al. (2022) have advanced this approach to explore employee search for management innovation. We see great promise in this approach because it can help us conceptualize organizational phenomena from multiple levels and theorize about the importance of different contextual factors based on how psychologically far away they are from the focal unit or level of analysis.

3. Some conceptual mechanisms that can explain the multilevel nature of organizational phenomena

Organizational phenomena are nested and knotted, that is, shaped by various factors from different levels of analysis, which inherently makes the complex nature of most organizational phenomena multilevel (Hernaus et al., 2020). Some phenomena, also called global unit properties (Kozlowski & Klein, 2000), inherently or intrinsically originate at higher levels, such as firm performance, national or regional laws and regulations, industry standards, societal regimes, and the characteristics of space, such as office environment etc. Often, however, the phenomena of interest to organizational researchers do not inherently exist or reside at higher levels; instead, they emerge at higher levels due to, for instance, organizational members being exposed to the same context. Working in the same environment or context means that employees and teams will likely develop a shared understanding of different organizational phenomena surrounding them (Bliese, 2006). For instance, having the same leader or following the same rules and procedures will likely lead

to greater similarity in how individual employees (working for the same leader) interpret their environment; hence, organizational phenomena may emerge across different levels. Theories such as social information processing (Salancik & Pfeffer, 1978) and the attraction-selection-attrition model (Schneider, 1987) have been commonly used to explain such emergence (see also Kozlowski and Klein [2000] for a comprehensive summary of different models of emergence). These theories suggest that, over time, employees will likely share their perceptions of the environment in which they work because they discuss practices, policies, procedures, and other vital aspects of their work and ultimately reach a consensus (i.e., social information processing). However, those who still differ will likely leave the organization, as explained by the selection-attraction-attrition model.

Returning to the earlier example of organizational culture, this construct is conceptually an organizational-level construct, which, in quantitative research, is most often operationalized by aggregating individual employee perceptions of organizational values and assumptions to the organizational level using one of the composition models discussed previously (Chan, 1998). The underlying assumption is that because employees are exposed to the same wider organizational environment in which basic organizational assumptions, values, and beliefs (i.e., key defining features of organizational culture; Schein, 2010) are enacted, they develop shared perceptions of organizational culture. The same rationale could be applied to study individuals' shared perceptions of other aspects of their environment, for instance, how work colleagues are collectively burnt out, which was found to significantly predict individual burnout experience (Gonzalez-Morales et al., 2012).

The contagion process is another mechanism that has been used to explain how phenomena emerge across multiple levels. Generally speaking, this process could also be explained by the fact that employees and teams work in and are exposed to the same context; however, the process of contagion can more explicitly and richly explain how higher-level

phenomena may emerge from phenomena that are inherent at lower-levels, such as emotions. A substantial amount of research around workplace emotions and affective outcomes at higher levels has been driven by the idea that employee moods, emotions, and other affective experiences within a team or an organization can be spread to other employees through the process of emotional contagion through which, for instance, employees mimic the moods, emotions, and affective states of their colleagues (Barsade, 2002). Thus, through emotional contagion, an individual's positive mood may cross to other team members and emerge at the team level as a collective positive mood (Bakker et al., 2009; Menges & Kilduff, 2015).

Working in the same environment, where contagion is likely to occur, fosters social interaction between employees within teams and organizations. Such social interaction can explain the emergence of certain higher-level phenomena, such as a transactive memory system, which refers to a shared division of cognitive labor (Lewis & Herndon, 2011). The transactive memory system is an emergent state that cannot be traced to any individual member alone. Conceptually, it exists because team/organizational members interact and develop a shared or collective system to encode, store, and retrieve vital information to complete their tasks. Similarly, group potency (i.e., a team's ability to complete a wide range of tasks; Stajkovic et al., 2009) and team reflexivity (i.e., a degree to which team members reflect upon team functioning; Schippers et al., 2015) are team-level phenomena that cannot be traced to any individual member alone – they exist because team members engage in social interaction as they work on their common goals and tasks.

In summary, some organizational phenomena such as global unit properties are inherently conceptualized at higher levels (see Kozlowski & Klein, 2000), whereas others may originate at lower levels, but emerge at higher ones due to the team members' exposure to the same environment, where contagion might take place as team members interact to fulfil their individual, team, and organizational goals. In quantitative research, where higher-level

phenomena are operationalized by means of lower-level data, the theoretical justification for emergence is directly linked to composition models and data aggregation (Chan, 1998), as also illustrated in Figure 1. In mixed-methods and qualitative research, scholars tend to have more flexibility to address contextual and emergent effects of their studied phenomena to generate multilevel theorizing (see also Köhler [2024] in this management focus).

4. Directions for future multilevel research

Future research could address several alternatives for multilevel theory, measurement, and analyses. We are especially excited about the untapped potential for using mixed-methods and qualitative multilevel approaches to study important and interesting research questions. For instance, qualitative methods can empirically address the reciprocity of contextual and emergent effects (Kozlowski et al., 2013) as well as temporal change trajectories that may be especially difficult to predict, and are often messy and non-linear. A good example here is a comparative multilevel analysis (Denk, 2010), that is, a fuzzy-set multilevel qualitative comparative analysis (QCA), which enables scholars to study synergetic effects of configurational variables among different levels (Thiem, 2016).

We also see substantial potential in conducting multilevel intervention studies (see Hall et al., 2018; LeNoble & Hudson, 2022) to advance our understanding of how different contextual characteristics across different levels may influence or explain the effectiveness of intervention programs. Drawing from Bronfenbrenner's (1977) socio-ecological systems perspective, such (quasi-)experimental studies could systematically assess how factors from multiple systems may affect the intervention outcomes. In addition to such contextual effects, multilevel intervention research could also address how and why certain effects emerge as a result of intervention. To this end, analytical advances from healthcare research could be coupled with mixed-methods or qualitative approaches, such as observations at multiple

levels (see Hall et al., 2018). This area of study is of utmost importance as it can provide valuable insights into the effectiveness of interventions in the organizational context.

Moreover, similar to Aguinis and Molina-Azorín (2015), we also see potential for mixed-methods multilevel research to better align multilevel theorizing with empirics. Such research designs "incorporate both qualitative and quantitative data and analytical tools" to provide meta-inferences about diverse aspects of a multilevel phenomenon (Headley & Plano Clark, 2020, p. 146). For instance, Hitchcock et al. (2021) demonstrated how to run hierarchical linear modelling (HLM) with quantitized qualitative data. Another interesting methodological advance was recently made by Meuer and Rupietta (2017), who showcased how we can integrate QCA and HLM for multilevel research. Other novel approaches, such as mixed-method social network analysis (Pantic et al., 2023), were also conceptualized in related disciplines yet the multilevel lens is still to be introduced in these approaches. Lastly, recent developments in text mining (Hickman et al., 2022), which can help analyze and quantify lengthy text-based documents and other archival data, seem particularly promising to advance mixed-methods multilevel research.

In Table 1, we summarize suggested directions for future research and highlight their potential impact on the field of multilevel organizational phenomena. If pursued, these directions could significantly advance our understanding of stakeholder influence and organizational strategy development.

Insert Table 1 about here
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5. Overview of papers in this management focus

The papers in this management focus significantly advance our knowledge of multilevel organizational phenomena by mobilizing diverse methodologies. The first paper uses a systematic literature review and the lens of social network and resource dependency

theories (Fares, 2024) to develop a novel multilevel typology of stakeholder influence. This typology integrates micro- (e.g., the influence between stakeholders embedded within the firm), meso- (e.g., the dyadic influence between a firm and its stakeholders), and macro- (e.g., the role of macro-level factors, such as political and technological in influencing stakeholders) level perspectives on understanding stakeholder influence. Using network betweenness centrality (i.e., "*the extent to which an actor lies between others who themselves are disconnected*") (Fares, 2024, p. 12) and closeness centrality (i.e., the extent to which an actor is close to other actors) as core micro-level mechanisms, the typology theorizes about four influence strategies, such as direct withholding, direct usage, indirect withholding, and indirect usage.

De Keyser et al. (2024) present a unique longitudinal qualitative case study of the diamond trading industry, examining micro and macro-level influences on organizational strategy over time. By unpacking the temporal influences of multilevel contexts on strategy trajectories, their findings lay the foundation for a multilevel process model of organizational strategy comprising four phases: symbiosis, lock-in, knock-on, and discordance. In each phase, three mechanisms can elucidate the evolution of the organizational strategy over time, such as multilevel balancing between micro and macro contexts (i.e., how bottom-up and top-down influences are managed in organizations), strategic rendering (i.e., how organizations implement such multilevel arrangements within their strategy), and contextual rippling (i.e., how the multilevel arrangements reciprocate implementation within the larger system). This paper underscores the dynamic nature of micro- and macro-level influences on organizational strategy. It explicates the necessity of studying the interplay between both to comprehend the process of organizational strategy development.

Next, using content analysis and system dynamics modeling, van Oorschot et al. (2024) examine the impact of changes in sustainability reporting standards on the

transparency of firm sustainability reports over time. The analysis of sustainability reports of 15 organizations in Norway from 2010-2020 showed that whereas the number of sustainability-related statements increased substantially, the transparency of these reports did not, despite the standards becoming more comprehensive. These surprising results were unpacked by exploring the interactions between stakeholders across multiple levels, such as organizations developing sustainability standards, reporting organizations, and the audience targeted by these reports using a system dynamics model. They found that with the release of new standards, the reporting organizations struggled to make their reports more transparent, which led to standardization organizations developing more comprehensive and specific standards, making transparent reporting even more difficult. As the authors point out, their study shows how "*micro-phenomena (i.e., readers having difficulty evaluating sustainability reports) are embedded in macro-contexts (i.e., complexity or density of sustainability reporting standards), and how macro-phenomena (i.e., generation of more sustainability reporting standards) emerge through the interaction and dynamics of lower-level elements (i.e., stakeholders' impaired judgment of organizations' sustainability performance)*" (van Oorschot et al., 2024, p. 2).

Finally, Köhler (2024) provides much-needed guidelines and advice regarding how to rigorously design and conduct multilevel qualitative research while at the same time acknowledging the diversity and richness of qualitative methodological approaches. Illustrating the rationale of methodological choices in one particular research case, this paper helps scholars appreciate different options as they embark on a multilevel qualitative project about the a) characteristics of the explored phenomenon and its levels of analysis as well as its core influences (and their levels of analysis), b) considerations regarding the research design, including choosing the appropriate and relevant research setting and sample as well as time periods to study the chosen phenomenon and its influencing factors, c) data collection

considerations related with the nature of conducting observations, interviews, and archival data, and d) considerations related with data analyses. We predict that this paper will be the primary source of inspiration for qualitative researchers interested in conducting rigorous multilevel research in the future.

6. Concluding remarks

The diversity of papers we have received for this management focus shows the vibrant nature of multilevel research across management and organization studies. We hope this management focus will push for more multilevel qualitative and mixed-methods research, which is much needed to address complex business and societal challenges. However, we should also note that mixed-methods multilevel research does not represent a straightforward road. Instead, we cannot agree more with Eckhardt et al. (2021) to favorize simplicity/ parsimony over complexity in conceptualizing and delivering multilevel research.

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Table 1

An overview of some current issues and how to address them in future multilevel research

Some current issues in multilevel research	**How to address them in future research?**
Disconnect between multilevel theorizing, empirical operationalization, and analyses	• Aligning multilevel theorizing with empirical operationalization • Developing novel measurement methods to operationalize multilevel phenomena • Developing novel analytical tools to align the analyses of multilevel data with multilevel theorizing • Using qualitative and mixed-methods multilevel approaches
Lack of multilevel intervention studies	• Designing intervention studies such that the role of contextual characteristics across multiple levels can be addressed • Exploring the intervention effects at the within-individual level with multiple measurement points • Using mixed-methods to assess the effectiveness of interventions

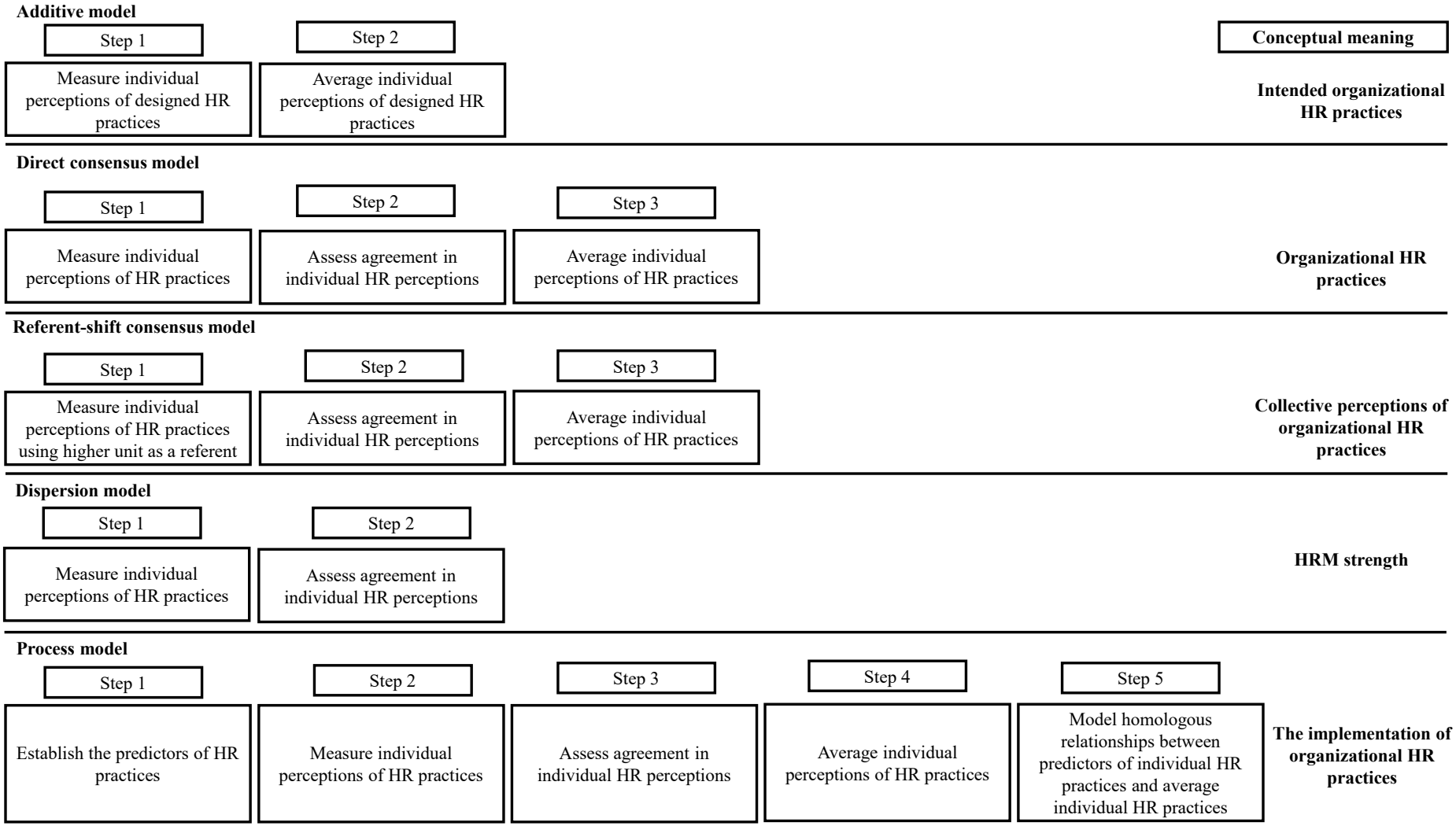

Figure 1. Summary of the typology of composition models using employee perceptions of organizational HR practices.

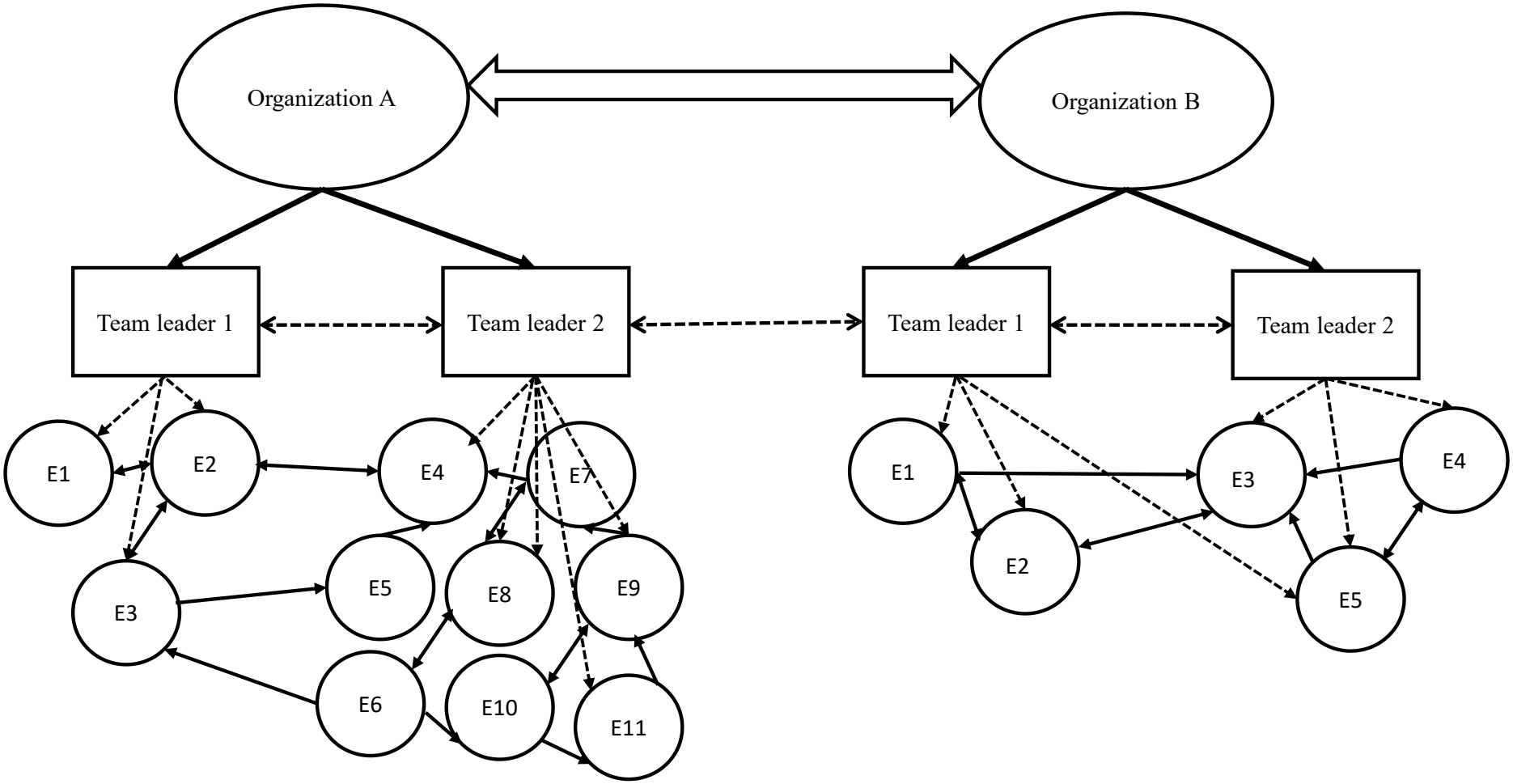

Figure 2. An example of a multi-level network. Ovals represent organizations, squares depict team leaders, and circles refer to employees or team members. Conducting such multi-level network analyses could help us study research questions, such as how leadership styles of team leaders and inter-team collaboration determine their team network characteristics and how they shape individual performance.

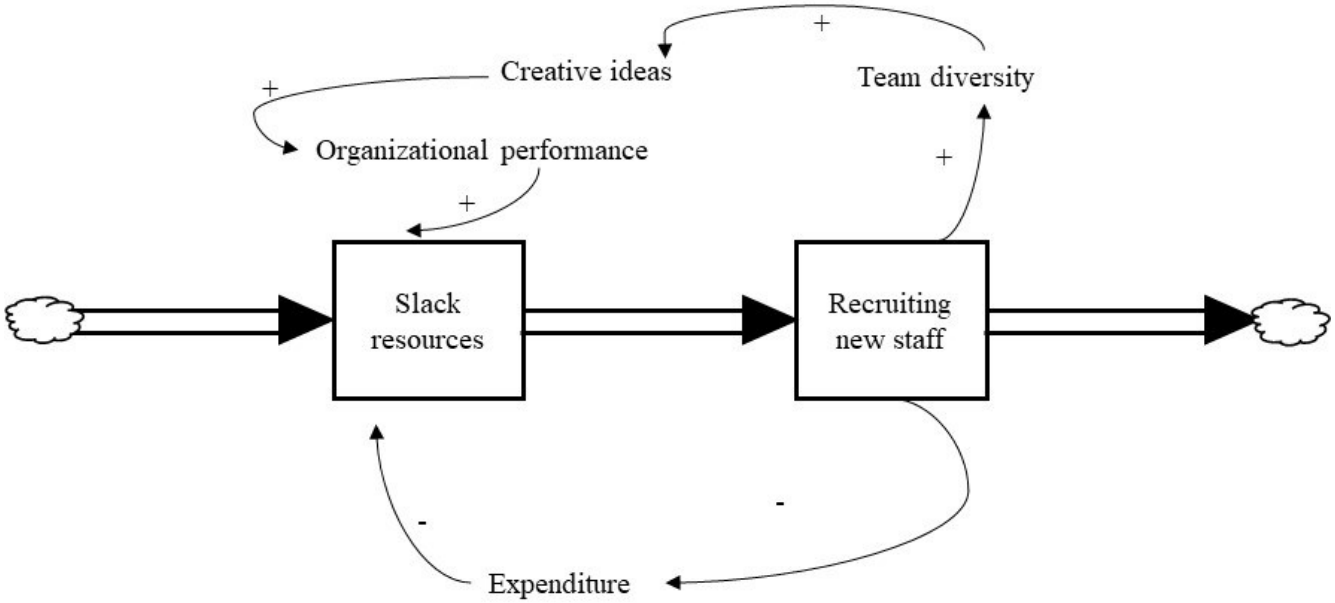

Figure 3. An example of a multi-level systems dynamic model to study organizational performance.

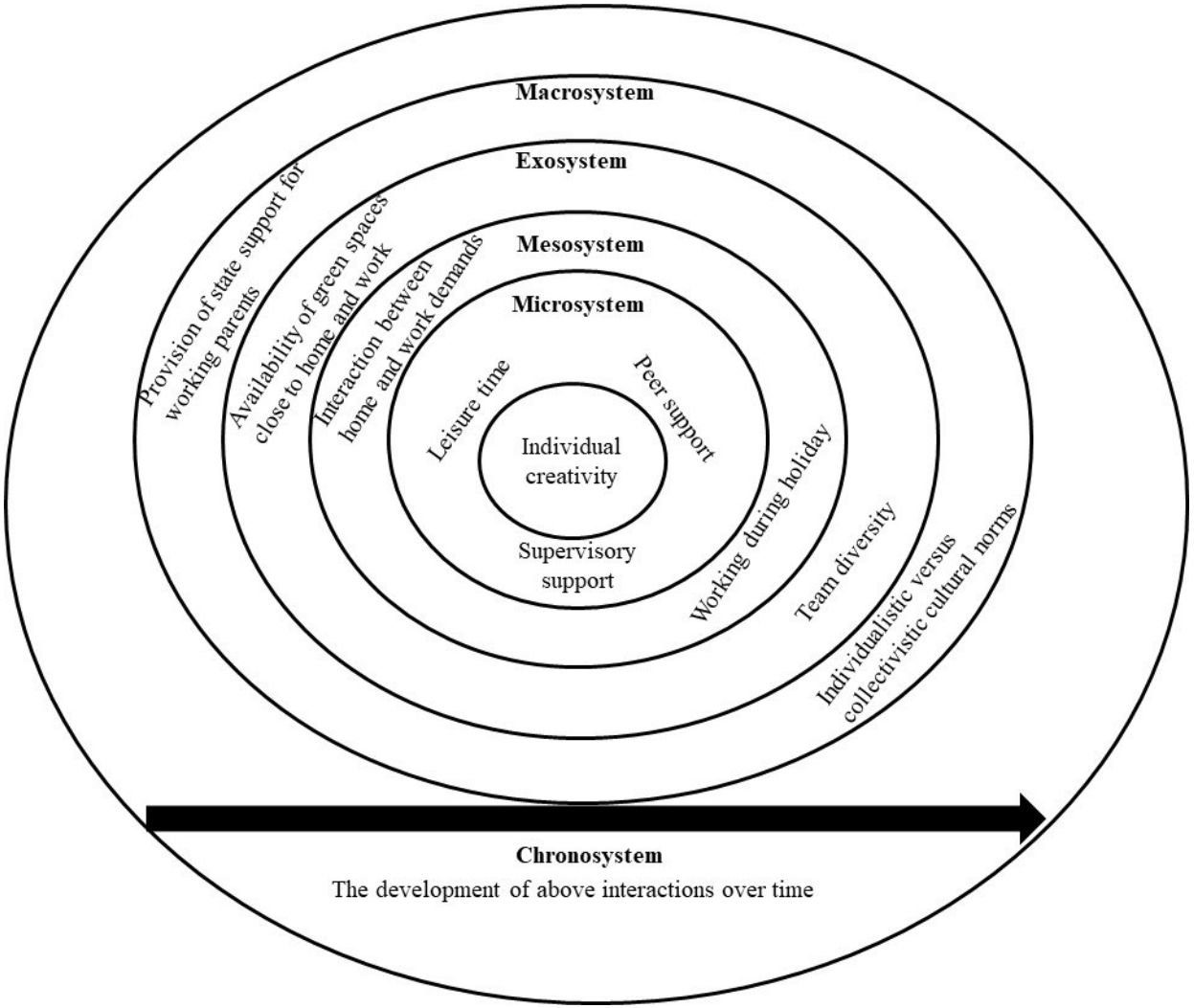

Figure 4. An example of a socio-ecological systems perspective to study individual creativity.

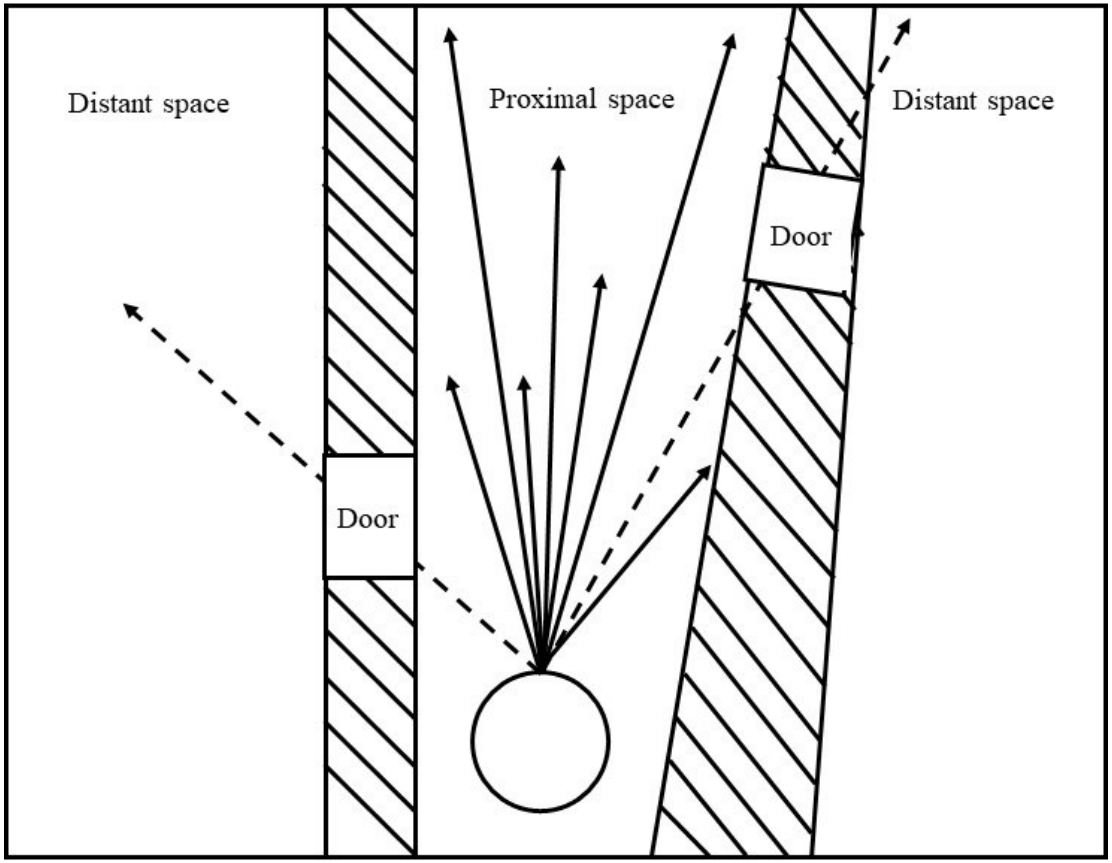

Figure 5. Using proxemic law to study how contextual factors shape individual behavior.
A circle represents an individual employee, who is predominantly moving with their most proximal space (i.e., the solid arrows). Once this space is exhausted, they will try to create doors to cross the walls, leading to more distal space. This figure was inspired mainly by Le Goff et al. (2022) and Robert et al. (2023).