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Interdependent Minds: Quantifying the Dynamics of Successful Social Interactions

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Abstract

Social interactions are a ubiquitous part of human life. They are also complex and dynamic, posing a challenge for traditional psychology methods. This article provides an overview of a dynamic systems approach to the study of social interactions that manages this complexity and enables the quantification of interdependence between people. We also discuss key empirical findings that demonstrate how different forms of interdependence and interaction dynamics shape social outcomes. Last, we highlight the utility of this approach for advancing theories of social behavior and practical application. By adopting this dynamic systems approach, researchers can gain a deeper understanding of the patterns underlying social interactions and test hypotheses about the mechanisms driving human connection and coordination.

Keywords

conversation, social interaction, dynamic systems, social connection

Social interactions are a profound aspect of human life. Through social interactions, people solve problems, generate innovative ideas, and foster a sense of meaning that is unattainable in isolation. But poor social interactions can also lead to misunderstanding, disagreement, or worse. It is both practically and theoretically essential to understand what makes an interaction satisfying and successful rather than frustrating or counterproductive.

Psychologists frequently study socializing in controlled laboratory experiments using simple tasks or imaginary scenarios. By reducing a social interaction to its most fundamental components, researchers aim to uncover the psychological building blocks of successful interactions. This approach has revealed foundational insights into how and why people think *about* other people (e.g., attitudes, cognitive biases, theory of mind) but does not explain how people think *with* other people. The distinction is important because cognition enacted with others is different from cognition enacted alone (Dingemanse et al., 2023; Schilbach et al., 2013).

An "interaction science" approach instead investigates socializing using naturalistic scenarios, such as unconstrained conversations, group decision-making, and complex problem-solving. This work reveals that the magic of a social interaction lies not in the sum of its parts but in the dynamic, emergent patterns *between* people (Asch, 1952; Wheatley et al., 2024). Despite the complexity of social interaction, these patterns are structured and quantifiable. This approach enables researchers to test predictions about emergent interdependent dynamics and how different types of interdependence influence interaction outcomes. In this article we discuss the logic of interaction science and empirical findings regarding social interdependence and make recommendations for

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how researchers can apply these methods to test theories of social behavior and cognition.

Social Interaction as an Interdependent Dynamic System

Imagine two roommates meeting each other for the first time, grabbing coffee, and discussing their interests, experiences, and preferences. This is mundane as far as human experience goes but nonetheless psychologically rich. Each roommate's mental state is shaped by past experiences, current motives, and external influences—including their interaction partner. These factors are numerous and interact in complex ways, changing from moment to moment. A goal to make a good impression can shift to a goal of negotiating who will get the bigger bedroom; emotions fluctuate; opinions of the other person are updated as information is shared. The bidirectional nature of this interaction also means that changes in one person can induce changes in the other, prompting further changes in the first partner, creating a deep feedback loop (Lehmann et al., 2024).

The multifactorial, dynamic nature of social interaction may appear too complex to model quantitatively. However, a dynamic (or dynamical) systems approach provides a framework to manage these complexities productively (Butler, 2011; Vallacher & Nowak, 1997). A dynamic system is any set of interdependent elements that change over time. This includes seasonal weather, a flock of birds, and human physiological rhythms. The behavior of dynamic systems can vary substantially, so the goal of dynamic systems analysis is not to predict specific system states but to uncover the system's internal mechanisms and organizational structure driving this variation.

Applying this approach to social interactions departs from traditional social-psychological analyses in three key ways. First, the social interaction as a whole is treated as the unit of analysis rather than the individuals within it. Second, variability in the system, even under consistent external conditions, is treated as meaningful behavior driven by intrinsic system mechanisms rather than dismissed as measurement noise. Last, despite the variety in system behaviors, the relationships among system components are quantifiable. Rather than explaining utterances or gestures of each individual, the key focus of dynamic systems analysis is the organization of the social system—how individuals vary in relation to each other. The type and strength of this interpersonal interdependence produces key outcomes of the interaction. In this way, cooperation, team performance, and meaning-making are emergent phenomena that are mutually constructed by the members of the system rather than properties of each individual separately (Linell, 2014; Stolk et al., 2022). Researchers can develop meaningful theories of social interaction by focusing on variables influencing the type and strength of this system-level organization rather than its individual components.

For example, imagine we want to test whether each roommate's affect influences how much they like each other after their first meeting. A traditional social-psychological analysis may focus on the average valence felt by both partners during the conversation to predict their mutual liking. This approach overlooks important aspects of the interaction. The same average valence could be calculated from steady or varying affect across time or from equal or divergent levels of positivity between the roommates. A single average valence value thus cannot distinguish between different interaction processes that may lead to the same outcome. A dynamic systems approach guides us to consider how the dynamics of affect in one person relate to the dynamics in the other and whether the kind and level of interdependence predict mutual liking.

Guided by this approach, researchers have identified distinct dynamics that characterize social-interaction systems. We describe these key findings next.

On the Same Wavelength: Synchrony as a State of Optimal Interaction?

Many social interactions are characterized by people's tendency to mirror one another's behaviors, physiology, and neural activity (Lotter et al., 2023; Mayo et al., 2021; Mogan et al., 2017). This phenomenon is most commonly referred to as "synchrony." Although some researchers have used other terms (e.g., "alignment," "coupling," "coherence," "coordination," "entrainment"), and some have used "synchrony" as a label for other operationalizations of bivariate relationships, we advocate for using the term "synchrony" only for its most common and specific definition to distinguish it from other dynamics. We define synchrony as fluctuations in one person's time data series that vary simultaneously and in the same way as those of another person. Formally, synchrony denotes a particular mathematical relationship between one person's data (e.g., thoughts, feelings, words, movements, physiology, brain activity), A, and another's, B, described by an identity function in which $A_t = B_t$ (Fig. 1a). This means the fluctuations in one person's time series vary at the same time and in the same way as the other person's.

Synchrony can manifest in various forms, including shared variations in one-dimensional, continuous, quantitative data such as skin conductance; similarities in multidimensional patterns such as brain activity; or matches in categorical classifications such as emotions,

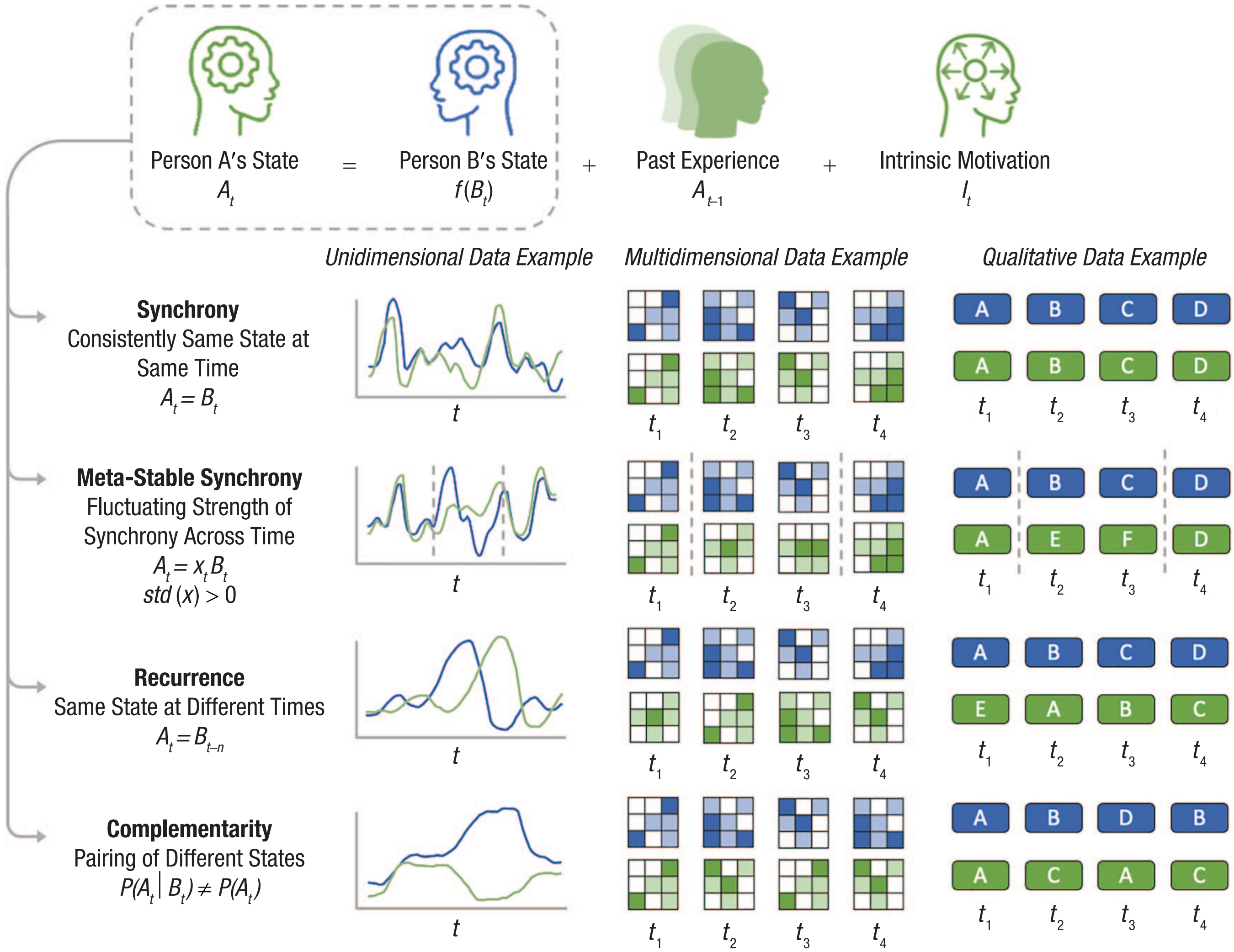

Fig. 1. Methods for quantifying dyadic dynamics. Numerous factors determine a person's dynamic psychological and behavioral patterns (A_t) during a social interaction, including the behavior of other people (B_t), past experience (A_{t-1}), and current intrinsic motivations (I_t). But the functional relationship (f) between A_t and B_t can take different forms. This includes (a) synchrony, in which both individuals vary simultaneously in the same way across time t; (b) metastable synchrony, in which the strength of synchrony x_t varies across time; (c) recurrence, in which the value of A_t echoes the value of B from some previous time ($t - n$); and (d) complementarity, in which the value of A_t depends on B_t in some nonlinear way but is not necessarily the same value.

gestures, or conversation topics. What matters is that the state of one individual is mirrored simultaneously in the other. Synchrony can also manifest at different time scales and levels of abstraction, from moment-to-moment actions to long-term alignment in personality traits. The degree of synchrony between A and B is quantified by how much variation in A over time is explained by B, akin to a classic Pearson correlation (Nastase et al., 2019).

Synchrony is widespread and often predicts positive outcomes such as prosocial behavior, bonding, interpersonal understanding, and positive affect (Mogan et al., 2017). Thus, understanding why people synchronize has become a major research objective. To explain its mechanistic role, prominent theories draw on the concept of predictive coding, in which brain activity reflects active predictions about the environment in addition to sensory processing (Huang & Rao, 2011). In the social world, neural predictions of other people include representations of their likely mental states and behaviors (Koster-Hale & Saxe, 2013; Thornton & Tamir, 2024). Theories of synchrony thus posit that when both interaction partners accurately predict each other, their neural activity will coincide (Kingsbury et al., 2019). This leads to, and is enabled by, synched physiological states and behaviors (Mayo & Shamay-Tsoory, 2024). In this way, synchrony can be viewed as a state of optimal social integration; people should endeavor to "get on the same wavelength." In the case of our roommate example, synchronization could indicate successful understanding of one another's thoughts, feelings, and goals while getting to know each other.

When Two Minds Are Greater Than One: Coordination Beyond Synchrony

Synchrony dominates the literature on dynamic social interactions. However, it is not the sole type of interdependence. Synchrony is not universally observed, and even when it is, the level of synchrony is often low. Additionally, a social interaction might have low levels of synchrony yet still be highly cooperative, generative, and connective. These realities suggest we need to consider other kinds of dynamics beyond synchronization. Below, we discuss types of *nonlinear* interdependence between people that have been observed in interaction.

Metastable synchrony

The concept of "metastable synchrony" is a slight adjustment to the basic synchrony model. In this type of relationship, the strength of synchrony between individuals fluctuates throughout the interaction (Fig. 1b). These fluctuations may occur as individuals prioritize different goals at different times, occasionally deemphasizing the drive to predict their partners' minds in favor of other objectives. For example, people often seek novelty in their interactions in addition to synchrony (Ravreby et al., 2022). Our roommates might initially synchronize by discussing predictable small talk such as the weather and then explore more novel topics such as recounting an unexpectedly humorous situation. Novelty requires that one person steer the conversation in an unanticipated direction rather than converging with their partner's previous location, temporarily desynchronizing partners. Yet people cannot leave their partner entirely behind—it is crucial to periodically mentalize about whether one's partner understands the new direction. This dynamic psychological balancing act between novelty and cohesion can shape how much people adapt to each other and synchronize moment to moment.

Traditional correlation-based measures of synchrony are calculated as a single average score across partners' entire time series. This approach cannot distinguish consistently moderate synchrony from metastable variation, in which periods of high synchrony alternate with periods of divergence. Instead, temporally resolved measures of synchrony can identify fluctuations in synchrony across time. Mathematical tools that provide such answers include sliding window correlation, phase synchrony (Glerean et al., 2012), or wavelet coherence (Zhang et al., 2020). These analytic methods quantify synchrony moment to moment, enabling researchers to probe whether sustained average synchrony or flexible switching between mutual attention and individually driven exploration is more important for good outcomes. Studies of dynamics in eye gaze (Mayo & Gordon, 2020), foraging behavior (Laroche et al., 2024), pupillometry (Wohltjen & Wheatley, 2021), and neural fluctuations (Jiang et al., 2012) during naturalistic interactions suggest that metastability can enhance bonding and task performance. As relationships become more secure, periods of divergence may become more frequent relative to periods of synchrony because of less uncertainty about one's partner or lower need to actively model them (Nguyen et al., 2024; Speer et al., 2024).

Recurrence

Synchrony and metastable synchrony identify when two individuals express the same states simultaneously. However, partners also mimic each others at nonconcurrent times (Fig. 1c), a phenomenon called "recurrence." A restrictive version of recurrence is when there is a consistent lag between one individual's signal and another such that they would be synchronized if this lag were resolved. This has been identified in neural patterns between a teacher and learner where the strength of lagged synchrony between a teacher's and learner's brain patterns predicts effective learning (Zheng et al., 2018), reflecting either the teacher anticipating a later signal in the student or the student following the teacher. Recurrence also occurs at variable time shifts, when interaction partners influence each other's behavioral repertoires or the probabilistic mappings between situations and reactions. This is evident in linguistic utterances during conversation: Vocabulary and grammar used by one partner shapes that of the other, refining what is talked about and how. This reduces the uncertainty of semantic meaning between people (Pickering & Garrod, 2004). Nonverbal behaviors may also recur. For instance, if one roommate uses particular facial expressions to convey a certain meaning, the other roommate may adopt these same gestures later to increase communication efficiency.

Tools such as recurrence quantification analysis can identify this dynamic by quantifying the proportion of signals from one person that are repeated by another at any point by another (or within a certain time lag; Duong et al., 2024). This approach has revealed interpersonal influences in facial expressions (Varni et al., 2020) and language (Dale & Spivey, 2006).

Complementarity

The dynamics discussed above describe how interacting people align their internal states and behaviors. However, there are also situations in which differentiation, rather than alignment, is beneficial. In these cases, we would expect interdependence in the form of complementarity rather than matching, where one person's state influences the probability distribution of what separate state the other person might experience (Fig. 1d).

For example, imagine our roommates now have an established relationship, with shared mental models for effectively living with each other. It is cleaning day at the apartment, and one roommate starts vacuuming. Rather than grabbing another vacuum to mimic this behavior, the second roommate scrubs the kitchen to enhance cleaning efficiency. In this way, the roommates align on the more superordinate goal of household maintenance but use different concurrent actions to achieve it (Goldstone et al., 2024). In another example, if one roommate is having a bad day, the other mirroring this negative state could lead to rumination and relationship dissatisfaction, whereas resisting emotional contagion could enable them to help their roommate out of the slump.

Quantifying complementarity requires detecting a nonlinear dependency between one person's state and another's. Metrics such as mutual information do so using probability. This method asks how much the value of one person's state influences the probability distribution of another person's state (Timme & Lapish, 2018). Mutual information is therefore a flexible method for detecting traditional cause-and-effect relationships between specific interpersonal states (e.g., Person A is likely to feel defensive when Person B feels angry), synchrony (e.g., any emotion in Person A is likely to be mirrored in Person B), and general complementarity (e.g., any emotion in Person A is likely to have a complement in Person B). The differences between these cases can be identified by the strength of the mutual information score (general complementarity/synchrony across all possible states would result in higher mutual information) and by investigating which states are most likely to be paired.

Hidden Markov models, a statistical method used to detect reliable and repeating state sequences within a multidimensional system, are another technique for this purpose (Visser, 2011). By treating multiperson configurations of the whole social unit as system states, one can find which and how many interpersonal role assortments reliably occur and whether the frequency of these particular dyadic states matters for outcomes. For example, particular listening-speaking dyadic states in patient-therapist interactions have been identified as relevant for depression recovery (Hale & Aarts, 2023). More generally, when particular state matching is not observed, the concurrent timing of state *switches* between interaction partners may indicate their level of sensitivity to each other.

Utility of Interpersonal Dynamics for Advancement in Psychology

In this article, we have described a dynamic systems approach for studying social interactions. Although this approach is not new (Vallacher & Nowak, 1997), it remains relatively uncommon among social psychologists despite its advantages for describing psychological processes in naturalistic interactions. We have also clarified different types of interdependence that structure interpersonal behavior and identified associated tools for measuring them. This approach helps researchers describe psychological processes manifesting in naturalistic interactions, improving our understanding of what it means to be a social species. This approach is also useful for inference and theory building. By formalizing and quantifying these dynamics, researchers can develop precise computational theories of the cognitive processes facilitating social success (Mayo & Shamay-Tsoory, 2024) that are more falsifiable than verbal theories.

For example, one area in which dynamic systems approaches are advancing theoretical development is in the study of social learning. Prior work suggests that a learner's success depends on their attention, motor coordination, and theory-of-mind capacities. However, less is known about how a teacher *and* learner mutually adapt to and integrate each other's knowledge (Pan et al., 2022). Investigating the level and type of interpersonal dynamics in interactive learning allows researchers to examine how individual capacity versus environmental factors versus group adaptability matters for successful learning, whether effective teachers lead or react to learners, when low-level mimicry turns into high-level understanding, innovation, and so on.

The measurement of interdependence dynamics may also be useful in practice, such as for the treatment of social dysfunction in disorders such as autism and borderline personality disorder. Although much of psychiatric theory assumes the origination of social problems is within a patient's own cognitive functioning, an alternative perspective characterizes social dysfunction as an interpersonal misattunement—a disruption in the initiation or maintenance of interpersonal dynamics that facilitate social goals (Bolis et al., 2022). This approach shifts the focus from the individual to the dyad and suggests that patient distress may arise from *collective* dysfunction. Effective intervention should thus prioritize enhancing the collective functioning of patients *and* their social partners—treating the patient alone is not enough.

Additional applications include developing artificial agents capable of seamless collaboration with humans in multiagent tasks. Rather than programming these agents to produce the vast space of possible actions via extensive decision logic, researchers could design the agents to adapt to human partners' behaviors through particular dynamics. This may facilitate more efficient cooperative agents. Such efforts have already shown promise in motor coordination (Dumas et al., 2014) and virtual shepherding tasks (Nalepka et al., 2019).

Social interactions can be a source of enjoyment, innovation, achievement, or distress. They also represent a crucial frontier in the scientific quest to understand human psychology. We believe the key to this domain lies in the dynamics between people. By understanding these processes, researchers can develop new theories and applications to enhance communication, collaboration, and connection in real-world interactions.

Recommended Reading

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Butler, E. A. (2011). (See References). Primer on using dynamic systems approaches for studying interdependence between people that is specific to emotions but can be applied to other variables of interest as well.

Wheatley, T., Thornton, M. A., Stolk, A., & Chang, L. J. (2024). (See References). Accessible overview of the current state of theory and methods in interaction science.

Transparency

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