Complexity

Complex Dynamical Systems in Human Development

Lead Guest Editor: Ralf Cox
Guest Editors: Ruud den Hartigh, Michael Richardson, Chen Yu, and Till Frank

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Editorial

Complex Dynamical Systems in Human Development

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Researchers from the complex dynamical systems perspective seek their explanations of human behavior and development in the dynamical interactions across many levels in an active, situated individual. That is to say, behavior and development are both constraining and constrained by the continuous exchange between a myriad of processes distributed across brain, body, and environment. This fundamentally questions the more traditional rationale that behavior and development of any kind can be explained by targeting a low number of domain-specific, static components or environmental factors [1–5]. In such a mechanistic approach, components are typically thought to exert their causal effects in a chain-like fashion [e.g., [6]], and development is explained by the function and place of the components in the chain. However, compiling evidence demonstrates that human behavior and development are dynamic, multiscaled, and emergent phenomena. It is for this reason that they should be studied from a complex dynamical systems perspective.

In order to address the massive interactionism that underlies behavior, and how it leads to developmental changes, we need a conceptual and methodological framework that can capture properties such as nonlinearity, self-organization, pattern formation, attractors, nested time scales, fractal scaling, and (inter-personal) synchrony. These properties have been widely observed in the domain of human development [7, 8]. Therefore, techniques are needed that enable a detailed analysis of the temporal structure in time series and that can handle both intraindividual and interindividual variability in developmental datasets, preferably in combination. Intraindividual variability needs to be studied both at the shorter timescales of the unfolding behavior and at the longer timescales of the developmental changes. Interindividual variability is a typical (almost defining) feature of development and needs to be addressed in any serious account of a developmental phenomenon. Importantly, both types of variability underline the importance of the complex dynamical systems perspective.

The properties of complex dynamical systems mentioned above can be detected and quantified by using techniques from the toolbox of nonlinear dynamics [9]. In the social sciences there is an increase in the use of nonlinear time series analysis and dynamical modeling as a means to study human development. Advancements are made in developing and applying techniques such as recurrence quantification analyses and longitudinal network modeling. The application of such techniques has led to insights in human developmental processes, which would not come to the fore with more "traditional" techniques [10–13].

This special issue has brought together a number of interesting articles that showcase the various methodologies related to the complex dynamical systems perspective and how they can be applied on a wide range of topics. The collection of papers demonstrates how the complex dynamical systems perspective can be useful in two ways: firstly, by advancing theoretical insights into human development, leading also to novel research questions; secondly, by offering a rich set of related analysis and modelling techniques that can be applied to human data, giving rise also to innovative data-collection procedures. Seven articles were published out of the many articles that were submitted to this special issue from all around the world. The quality and diversity of the articles denote the impact and relevance of complex dynamical systems in human development.

In the article "Does Competence Determine Who Leads in a Dyadic Cooperative Task? A Study of Children with and without a Neurodevelopmental Disorder" by R. Vink et al., the collaborative dynamics of typical children as well as children with a neurodevelopmental disorder is investigated. In order to determine dyadic synchronization, children's postural sway, while they perform tangram puzzles together, is analyzed using recurrence quantification analysis. Interesting differences between typically developing children and children with neurodevelopmental disorders are revealed, in terms of the relation between the dyads performance, the ability level of each dyad members, and who leads and who follows in the interaction. The authors stress that the analyses they applied are insightful, and that they are relevant because of the importance of cooperative learning for academic performance.

In the article "Development and Complex Dynamics at School Environment" by M. A. Fuentes et al., the complex dynamical systems approach is used to study peer interactions in a learning environment, but with a focus on social network plasticity. In their work the authors assess the effectiveness of a school-based intervention. Quantitative work is presented on the impact of cooperative and self-awareness activities on behavioral plasticity of social relationships amongst 6-7-year-old children. Complex networks and game theory are employed to analyze the changes in the patterns of social relationships due to the intervention, in comparison to a control group. The intervention proves to have positive effects on social interactions, amongst other things by enhancing children's positive networks.

In the article "Socioemotional Dynamics of Emotion Regulation and Depressive Symptoms: A Person-Specific Network Approach" by X. Yang et al., experience sampling data of over one year from a large group of participants is reported in the context of depression. The socioemotional processes of daily social interactions and the regulation of negative emotions are studied, with special emphasis on intraindividual differences and change. Relations are revealed between depressive symptoms on the one hand and the length of recovery time and stressful life events on the other. The person-specific network approach to study (changes in) emotion regulation in individuals, as applied in this article, exemplifies the complex dynamical systems approach to the study of psychological health.

In the article "Self-Esteem as a Complex Dynamic System: Intrinsic and Extrinsic Microlevel Dynamics" by N. M. P. de Ruiter et al., the focus is on intraindividual variability and attractor states of (state) self-esteem in adolescents. The authors develop and test their Self-Organizing Self-Esteem model, which is based on interactions between a person's social context and the intrinsic dynamics of self-esteem resulting from higher-order self-esteem attractors. Using Kohonen's self-organizing maps and state space grids, this study tests the levels of self-esteem attractors and how this determines the influence of changes in the immediate context (e.g., parental support) on self-esteem variability.

In the article "Developmentally Changing Attractor Dynamics of Manual Actions with Objects in Late Infancy", J. I. Borjon et al. also focus on attractor dynamics, but in the context of infants' motor development. The authors are interested in how order in manual actions arises and seek its explanation through developmental changes in attractor dynamics. In a longitudinal study, they analyze the dynamics of manual actions during the first two years of infants' lives. The authors introduce and apply a new technique for studying attractors properties, like attractor size and dwell time, and show how these change across development. Their analyses are based on motion data of infants limb effectors while they interact with toys.

In the article "The Development of Talent in Sports: A Dynamic Network Approach", R. J. R. Den Hartigh et al. investigate talent development using a dynamic network modeling approach. Their dynamic network model predicts typical individual developmental patterns, which closely correspond to the patterns observed in different famous athletes. Next, the model is used to predict distributions of athletic achievements across sports, geographical scale, and gender, from Grand Slam victories in tennis (male and female), major wins in golf (male and female), goals scored in ice hockey (male), and goals scored in soccer (male). Overall, the dynamic network model provides a comprehensive framework to understand the theoretical principles underlying the development of talent.

In the article "Categorical Cross-Recurrence Quantification Analysis Applied to Communicative Interaction during Ainsworth's Strange Situation" by D. Lira-Palma et al., a novel analysis of a well-known paradigm in developmental psychology is presented: the strange situation procedure for assessing children's attachment quality. Categorical (cross-) recurrence quantification analysis is used to study synchronization in the communicative interactions during the unfolding of this procedure, for two children and their caregivers. The authors extract and compare several recurrence measures from the time series of verbal and motor behaviors, at both the individual and dyadic level. Results emphasize the role of interpersonal coupling and synchronization in the strange situation procedure, which is different for verbal behaviors than for motor behaviors and for caregivers and strangers than for children.

Conflicts of Interest

The editors declare that they have no conflicts of interest regarding the publication of this special issue.

Ralf F. A. Cox
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Research Article

Development and Complex Dynamics at School Environment

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In this work we use complex systems methodologies to analyze quantitatively the impact of an intervention involving cooperative and self-awareness activities on social interactions in children. The aim of this study is to evaluate behavioral plasticity of social relationships between peers in 6-7 year-olds who participated in the intervention conducted in a school context. The intervention consisted of 8 one-hour long sessions comprising mindfulness-based practices, collaborative activities that required cooperation, and perspective-taking instances in which children shared feelings, perceptions, and needs felt during the activities. We used complex network and game theory to evaluate pre-post-intervention variations. Social relationship was analyzed with a sociogram in both the intervention group and a control group which continued with regular classes. By means of the sociometric questionnaire we asked each child to mention which classmates he/she would choose as playmates and which he/she would not. Changes in the number of peers selected and rejected reflected changes in the pattern of social relationships pre-post-intervention. Our findings show that participating in the intervention positively modulated social interactions since we found an increase in the diversity and quality of positive links and a reduction in negative ones; a higher level of integration, indicated by enhanced positive networks where children with many positive connections tended to connect with those with few links; and more positive interactions between genders. These findings were not observed in the control group. Through the use of the mentioned methodologies, the current investigation provides new quantitative evidence of social network plasticity in children, an important topic which, to our knowledge, has been little studied. Results from this work indicate that positive transformations in social relationships can be fostered through the performance of this kind of intervention.

1. Introduction

It is increasingly clear that social and individual dynamics, as for example in children, involve complex interactions embedded in networks, where information flow creating emergent properties that can be studied using different quantitative techniques, as nonlinear science, network analysis, information theory, etc. [1]. Behavioral plasticity in terms of prosocial attitudes, i.e., changes in prosocial behavior that result from experience, has been recently demonstrated in young children (e.g., [2–4], Lozada, 2014; [5–7]). Several investigations showed that children display a great ability to modulate their behavior when they experience situations involving empathic concern, caring for others, cooperative activities, etc. In particular, emotional resonance between self and other enables the emergence of empathic concern [8, 9], which has been defined as the affective response related to the understanding of another's emotional state [10] and is a necessary condition for prosocial attitudes [11–15]. Interestingly, it has been observed that behavioral changes associated with prosocialness, positive social relationships, and emotional regulation are also accompanied by favorable effects on physical and psychological well-being (e.g., [3, 6]). Numerous investigations have shown that empathic concern for others and social network diversity can foster healthy states ([16–19], Pace et al. 2010, 2012; [20]). It has been proposed that social relationships protect physical health and well-being (e.g., [21–23]). Several researchers have demonstrated a relationship between social network size and diversity (social network structure) and the functioning of the immune system [24, 25] and HPA axis activity (e.g., [26–28]). Supportive social networks and positive relationships can act as a buffer against the potential negative effects of stressful events (e.g., [29, 30]). Growing evidence emphasizes the role of peers as buffers against stress in children [31–33]. Consistent with this, it has been found that altruism in human beings, which involves behaviors such as helping, sharing, comforting, and informing, tends to occur beyond reciprocity, kinship, or reputation in a higher proportion than predicted by evolutionary theory [34, 35]. This highlights the relevance of prosociality in human beings, suggesting that consideration for others can confer benefits not only on the receiver but also on the giver. In line with this, altruistic motivation has been shown to emerge at an early age; it has been observed that 18-month-old children spontaneously help nonfamiliar individuals [36, 37] and show empathic concern for those in distress [38, 39]. Interestingly, it has been found that children of less than 2 years of age exhibit greater happiness when sharing with others than when receiving treats themselves [40], and that babies of 3 to 10 months prefer helping situations to neutral or hindering ones [41, 42]. The above-mentioned investigations reveal the early emergence of prosocial attitudes and confirm their beneficial effects.

It has been proposed that social cognition is inseparable from processes of interaction with others (e.g., [43–45]). That is, cognitive agents are not passive data collectors who model the world, but active participants who enact a world in close connection with others (e.g., [44–46]). Therefore, social cognition involves not only understanding others but also understanding with others [45, 47]. Behavioral plasticity related to social interactions in children has been analyzed by the application of activities, which seek to promote relationship changes in controlled situations (e.g., [48]). Thus, observable changes are evaluated and compared before and after participation in a specific intervention. In earlier work with 6- to 7-year-old children we found that interventions involving mindful and cooperative activities, which favored self-connectedness and connectedness with others, enhanced generosity between peers [49]. Therefore, altruistic attitudes under anonymous conditions increased after the intervention. Similarly, when this type of intervention was performed in 7 to 9 year-olds, social relationships between peers improved and stress levels also decreased [48]. Other recent investigations showed that mindfulness-based interventions in preschool children fostered good health and social-emotional development [3]. In addition, other programs of activities involving self-awareness practices and caring for others (e.g., cognitive-based compassion training) favored prosociality, stress reduction (e.g., [6]), empathic concern, compassionate attitudes [5], and emotional regulation ([50], Flook et al., 2010; [51, 52]). Moreover, cooperative play increased self-confidence, prosocialness, and self-regulation in participants [53, 54]. These studies illustrate how mindfulness-based practices and cooperative experiences can promote prosocial behavior and well-being in children, highlighting the plasticity displayed at this early age.

Little is known about how behavioral interventions have the potential to change peer relationship networks in the sense of increasing socialization. However, while some studies have analyzed intervention effectiveness in improving peer relationships in children (e.g., [55]), few have proposed the theoretical-methodological approach of social network analysis to assess their effects (e.g., [56, 57]). It has been proposed that social network analysis could improve ways of testing the effects of behavioral interventions by considering interdependencies of peers network data instead of taking into account aggregation of individual characteristics (e.g., [57]). Social relationships in a group can be evaluated through the sociogram, a sociometric parameter which depicts the dynamics of social processes [54, 58, 59]. This trustworthy tool describes the social network of each child in a group, assessed by means of a questionnaire asking each child to say which peers they want to play with, and which they do not. When applying this measure in diverse instances within a certain group, the dynamics of social interactions can be assessed. Since this measure also identifies antagonistic interactions within a group, social exclusion and social integration can be recognized. Consequently, this measure illustrates social links within a group of peers, contributing to our understanding of the complexity and dynamic nature of children's social networks.

In the present work, *via* a case of study, we aim to further study the impact of experiences, which involve mindfulness-based practices and cooperative activities, which increase awareness of themselves and of others, on social interactions in 6-7 year-olds. Considering the beneficial effects of prosocial behavior, along with the behavioral malleability of this age, we evaluate social network plasticity in a formal education context. We carry out a short intervention, which consisted of 8 one hour long sessions comprising: mindfulness-based practices, collaborative activities, and perspective-taking instances that has previously proven to favor prosocialness between peers of this age (see, for example, [49]). Social network configuration is compared before and after the intervention in both an experimental and a control group. We expect to find that participation in the intervention will bring about an increase in the quality and diversity of positive social relationships between peers and a decrease in the negative ones. These potential favorable changes in the network configuration could support the implementation of this kind of intervention in educational settings which might improve social dynamics in children.

2. Methodology and Methods

2.1. Participants. This research was carried out with children aged 6-7 in a public school. All participants were all in good health, and there were no significant differences in body mass index or socioeconomic level. One class was selected at random as the experimental group, which included 24 participants (62.5% boys and 37.5% girls), and another class of 20 children (45% boys and 55% girls) formed the control group (which followed the regular school program). In the experimental group three researchers performed the intervention once a week, accompanied by the class teacher. The study was performed in accordance with the Helsinki Declaration, and all procedures were conducted with the written consent of parents and school authorities. The data collected were treated under confidential conditions.

We first interviewed each child individually to evaluate the sociometric parameter (see below). We then performed an intervention program once a week for 10 weeks, during which children carried out self-awareness practices and cooperative play and shared a moment of reflection. On conclusion, we conducted a postintervention individual interview, with the same content as the first.

By means of a sociometric questionnaire [54, 59] we evaluated social connectedness previous to and after the intervention in both experimental and control groups. In the individual interviews, children were asked to say which peers they would like to play with and which they would not like to play with. That is, children's answers referred to the name of peers selected or rejected to play with (in order to determine positive versus negative interaction links, respectively).

2.2. Intervention. The program consisted of sessions of 60 min each. Each one included three consecutive instances: an initial stage of self-awareness practices, a second stage of cooperative games, and a third stage of group reflection (as in [48, 49]). The first instance included breathing techniques and other mindfulness practices and exercises that involved slow, deliberate movements that children could focus on for several minutes. These practices helped children become more aware of moment-by-moment experiences. The cooperative games entailed playing in a collaborative way in order to achieve group goals, as conducted in Garaigordobil [54]. In the final instance, the children were invited to sit in a circle, and each child had the opportunity to express how they felt, say which parts of the game they enjoyed most and whether they preferred helping or being helped.

2.3. Social Network Analysis. We evaluated children's networks comparing the pre- and postintervention sociograms. Children's networks are represented by graphs $G(C, E)$ projected from the sociograms, where C is the set of children in the class and E the set of links between them. These links can be positive or negative, depending on the interaction between the children. We performed a detailed network analysis at different levels. At macrolevel, we computing metrics such as the average connectivity of children, their in-degree and out-degree (i.e., number of links arriving at a node and the number of links that leave a node, respectively), the density of the networks (i.e., proportion of existing links in relation to possible links), and their community structure (i.e., set of nodes that are more connected among themselves than with the rest of the network), using the algorithm proposed by Blondel, Guillaume, Lambiotte, and Lefebvre [60]. At mesolevel, we compute the correlation connectivity between children, using the degree assortativity, r, as the measure that captures these correlations [61]. At microlevel, we studied the triad configurations. According to Kadushin [62], the triad is one of the most important motif classes in social networks, since they represent the beginnings of a "society" that is independent of the links between dyads. The role of the children in these networks was also analyzed.

3. Results

3.1. Macroanalysis. We constructed negative and positive networks, NN and PN, respectively, for the control and experimental groups. NNs contain only links from a child (the source) who does not want to play with another (the target). In contrast, PNs are networks with links from children that want to play with other children. For both kinds of network we constructed two temporal graphs: one corresponding to the results of the first interview (preintervention measure) and the other to the second (postintervention measure).

Figure 1 shows the analysis of NNs and PNs before and after the intervention in both groups. The figure is divided into two: NNs at the left and PNs at the right. In both parts, again, two sections are plotted: the control group (left) and the experimental group (right). For each group we plot the parameter before and after the intervention. We observed that, in the case of average connectivity, $\widehat{k}$, in NNs, the number of negative links was higher (15.56%) in the control group in the second measure than in the first, with a mean of 2.250 and 2.600, respectively. However, in the case of the experimental group, this number was lower (39.34%) after the intervention than before, with a mean of 1.542 and 2.542, respectively. In the case of PNs, we observed that positive links increased in both groups but in the experimental group this increment was more marked (24.10%), with a mean of 10.375 and 12.875 before and after the intervention, respectively, in comparison with the control group (8.18%), whose means were 7.950 in the first measure and 8.600 in the second measure. The statistical analysis comparing the average in-degree before and after the intervention showed a significant increase in PNs (t = -2.66, p = .014) and a significant decrease in NNs (t = -2.326, p = .029) in the experimental group, whereas in the control group no significant differences were found between the first and second measure for either PNs (t = -.804, p = .432) or NNs (t = -.464, p = .648). The average out-degree before and after the intervention showed a significant increase in PNs (t = -4.678, p < .001) and a significant decrease in NNs (t = 3.464, p = .002) in the experimental group. In contrast, in the control group, nonsignificant differences were found in PNs (t = -1.51, p = .14) and NNs significantly increased (t = -2.101, p = .049).

A similar pattern was found for network density. The NNs of the control group were more "populated" with negative links in the second measure (density index increased from .118 to .137) whereas the opposite occurred in the NNs of the experimental group (density index decreased from .111 to .067). In contrast, in the PNs scenario, the population of positive links increased more notably in the experimental group (density index increased from .458 to .560) than in the control group (density index only changed from .418 to .453).

The community structure shows that the control group in the NN scenario decreases between the first and second

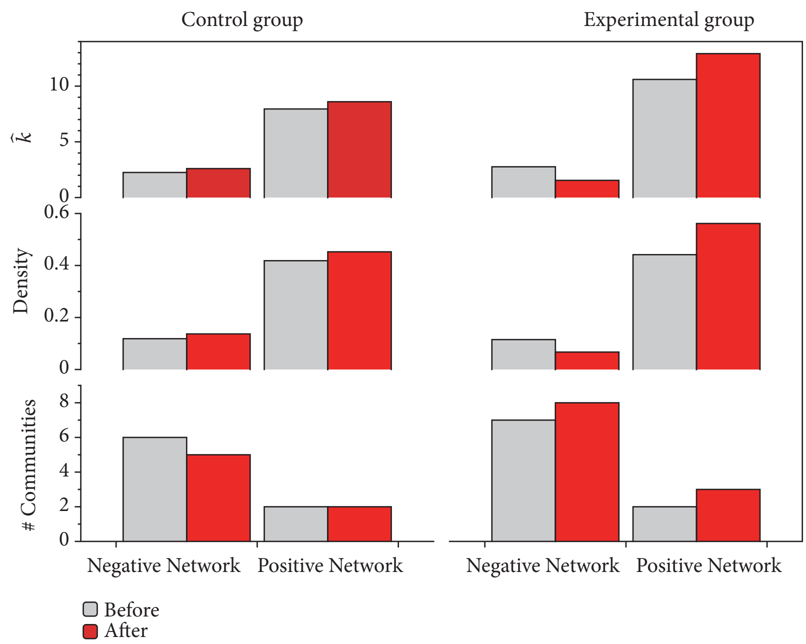

Figure 1: Network topological properties. Average network degree $\hat{k}$ (top), link density (mid), and number of communities (bottom), for control and experimental groups for negative (left) and positive networks (right).

measures. This means that, in the second measure, the negative links are less confined than before. The opposite occurs in the experimental group where negative links seem to be more confined in communities (more communities). It is important to note that the students maintained, on average, 71.8% of their positive relationships after the intervention. Also, 75% of the students with less positive relationships (than the average) before the intervention increased their positive preferences to 93.5% after the intervention. Only 28.5% of those students with more positive relationships before the intervention increased the number of their relationships, and they did it on average only by 16.4%. Obviously, the probability of choosing new positive relationships is lower in this latter group. The remaining 71.4% of this group maintained or decreased the number of positive relationships, although in an insignificant way. In the PN scenario, the number of communities increases in the experimental group, suggesting that the network of positive links presents a modular structure. The control group shows a similar tendency but to a lesser extent.

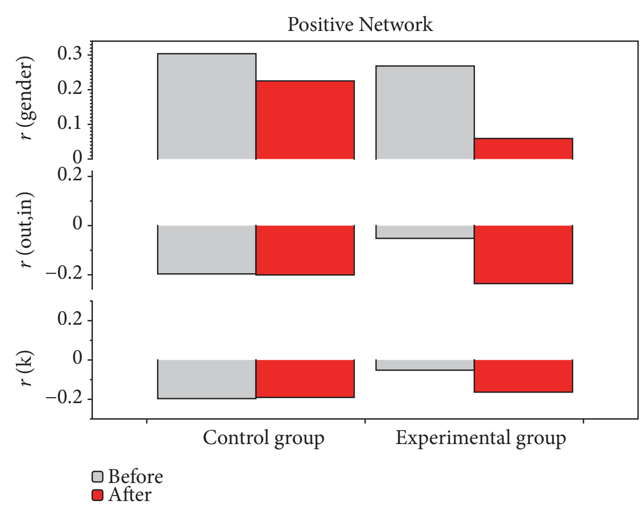

Figure 2: PN assortativity measure. r(gender) (top), r(out,in) (mid), and $r(k)$ (bottom) for control group (left) and experimental group (right).

3.2. Connectivity Correlation Analysis. We also developed an analysis of the correlation between children's connections using the assortativity index, r, which is a measure that captures the correlation between node properties [61]. Thus, in the scenario of symmetric connection (undirected network), if densely/poorly connected nodes are connected to other nodes with many/few connections, the network is considered assortative, $r > 0$. On the other hand, if densely/poorly connected nodes are connected with poorly/densely connected ones, the network is disassortative, $r < 0$. If no correlation is observed, $r \sim 0$, nodes do not have a link preference. In the asymmetric connection scenario (directed networks) all types of assortativity can be computed for PNs and NNs: r(in,in), r(out,in), r(in,out), and r(out,out) where the first element in the parentheses indicates the degree of the source node, and the second, the degree of the target node. We also performed correlation analysis by gender link preference.

No clear results were obtained for correlations in NNs, but we found some changes in the assortativity for PNs after the intervention (Figure 2). In the case of gender correlation we observed that, in the case of the control group, boys choose boys and girls choose girls; the correlation is positive ($r > 0$) before and after. However, in the experimental group

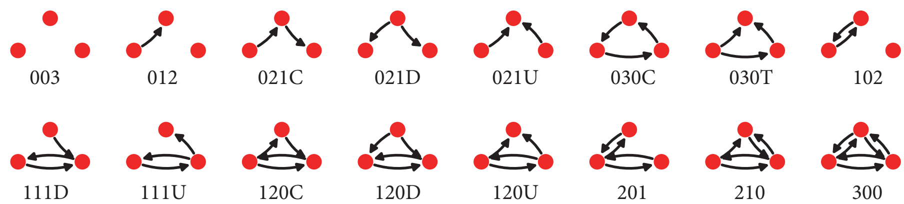

FIGURE 3: Triad configurations. 16 possible configurations of links between three nodes in a directed network.

gender correlation tends to disappear after the intervention (Figure 2, top).

The effect of the intervention on integration can also be observed in the correlation analysis for directed networks. In the case of r(out,in) we can observe that no change occurred in the control group after the intervention; the PN of the control group remained disassortative. However, the PN of the experimental group changed from uncorrelated to disassortative, suggesting the integration of children with few positive choices (Figure 2, mid).

Finally, in the case of the degree assortativity $r(\widehat{k})$ for the control group, it can be seen that no change was observed at the second measure. However, in the case of the experimental group after the intervention, the PN were clearly disassortative; the correlation was observed; i.e., children with many/few positive connections tended to connect with those with few/many links (Figure 2, bottom).

3.3. Network Motif Analysis. Considering the direction of edges, we can also explain the structure of the networks on a local scale (child to child). In particular, we are interested in motifs as local connection patterns such as functional units like feed-forward and feedback loops. As an example, we carried out our analysis looking for variation in the frequency of four specific triad configurations for PNs and NNs. In PNs we searched for configurations 210 and 300 (the last two triads of Figure 3), whereas in NNs we focused on configurations 021U and 111D.

As can be seen in Figure 4 (left), negative triad configurations (021U and 111D) showed an increment in the case of the control group, whereas in the experimental group these configurations showed a significant decrease. In contrast, positive triad configurations 210 and 300 (Figure 4, right) showed a stronger increment in the case of the experimental group.

3.4. Microanalysis of Group Class Networks. Finally, we studied the effect of the intervention on the role of children in their class groups. Figure 5 shows two rows of networks: the bottom networks display the NN (left) and PN (right) of control group class before the intervention, while upper ones represent the structure of the networks after the intervention. Each one of the networks is drawn in a hierarchical way: the more frequently chosen children are located at the top of the networks, while to the right are those who choose more children. For example, in the case of the previous PN (bottom right), the node “Va” is highly chosen by the rest of the class (high in-degree) but this node also chooses many children (high out-degree), in comparison with “Ar” who chooses fewer children to play with (low out-degree). However, like “Va”, “Ar” is also much chosen by the rest of the class (high in-degree).

It can be observed in the control group that negative leaders (“Am” and “Je”) continue with the same characteristics in both PNs and NNs throughout the study (they are on the top of both NNs and on the bottom of the PNs). In this PN scenario, “Am” and “Je” are poorly chosen by the class; however, they choose many of their classmates (they are located to the right of the layout before and after, close to the center).

Something completely different was seen in the experimental group (Figure 6, same layout distribution as Figure 5). Even though before the intervention the NN is practically an inverted image of the PN, as in the case of the control group where negative leaders are not positive leaders and vice versa, after the intervention the roles changed. New children appeared as negative and positive leaders, highlighting the effect of the intervention. Moreover, these leaders do not correspond to nonleaders on opposing networks as before. Finally, another effect of the intervention can be observed in the NN after the intervention. In this case, the nodes are concentrated on the left of the layout (i.e., they reject fewer than before).

4. Discussion

The methodologies used in this manuscript can be expanded in order to study other characteristics of human interaction in educational environment. The current study shows how self-awareness and cooperative activities enacted during an intervention increased positive social relationships between peers and diminished negative ones. Our findings suggest that the activities which involved working with others to attain shared goals positively modulated social interactions, highlighting the great behavioral plasticity of primary school children. Social network diversity and the quality of positive links improved after the intervention in the experimental group, whereas no such changes were observed in the control group. These outcomes were assessed by means of mathematical tools based on network theory, which made it possible to visualize the complexity and dynamics of children’s social networks. The model showed that, after the intervention, positive interactions enhanced (more dense friendship networks and increase in positive triad configurations), positive interactions between children of different genders increased (weakening same-gender preference), and negative

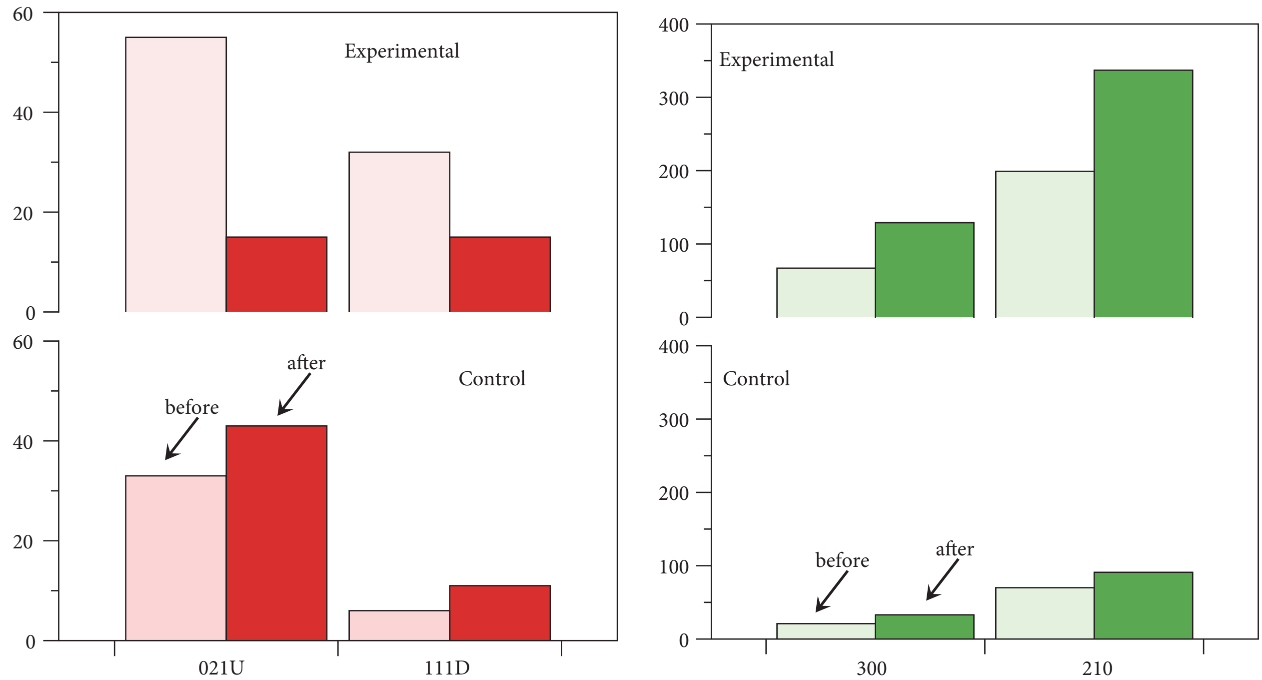

FIGURE 4: Variation in the number of triad configurations. Triads considered as negatives are shown in the left plot and positives on the right.

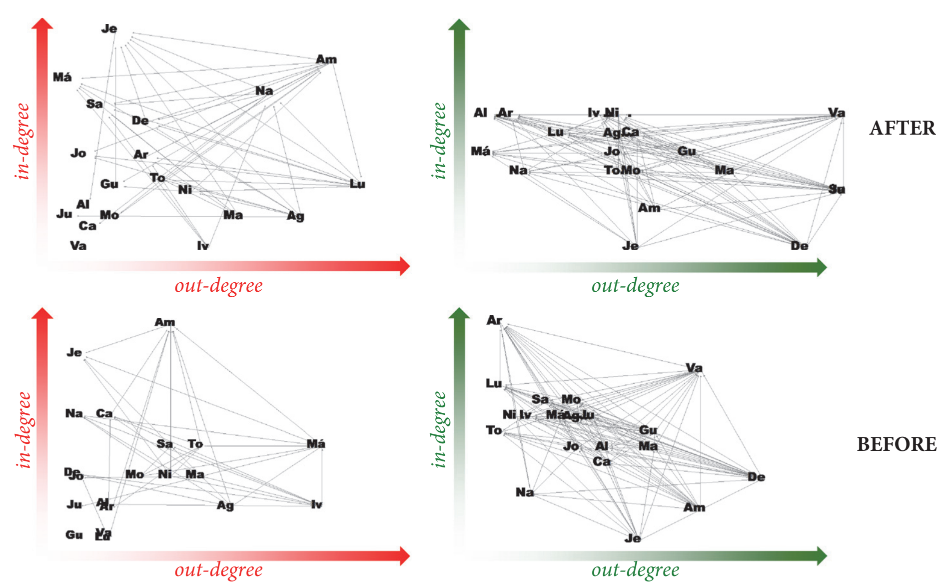

FIGURE 5: Control group networks. NNs (left) and PNs (right), in the first (bottom) and second evaluations (above). Network layouts show nodes which have a high number of in-degree connections located upper across the vertical axe and those with high number of out-degree connections located at the right of the horizontal axis.

interactions decreased (less dense enmity networks and decrease in negative triad configurations) and that children with many positive links connected with peers who had few links and vice versa. This may suggest the development of empathy on the part of the most frequently chosen children, allowing greater social integration. Likewise, both negative and positive networks were more confined within communities after the intervention, which could be indicating the emergence of a greater diversity of interactions between peers. In addition, the intervention allowed a roles' change in the group, given that new children appear as negative and positive leaders, that accounts their great plasticity.

The fact that this kind of intervention reduced negative interactions and increased positive ones agrees with previously reported findings suggesting that higher levels of social harmony can be promoted in schools. In addition, it has been found that this type of intervention can reduce stress levels (e.g., [48]), highlighting the significant impact

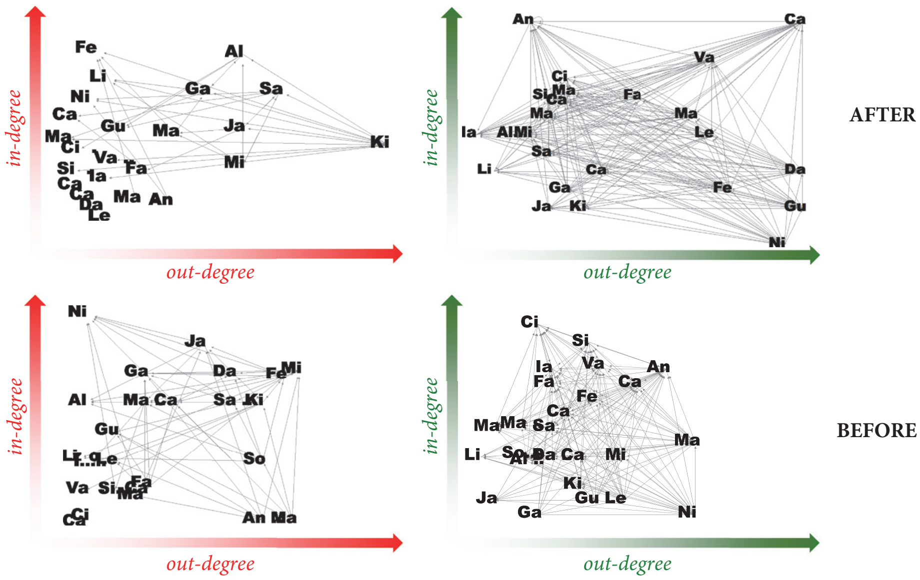

Figure 6: Experimental group networks. NNs (left) and PNs (right), before (bottom) and after (up) the intervention. Network layouts show those nodes with high number of in-degree connections located upper across the vertical axe and those with high number of out-degree connections located at the right of the horizontal axis.

of positive social networking and quality social relationships. These results further support the existence of the buffering effect of positive relationships, indicating the importance of implementing this kind of program during childhood. It is interesting to note that these findings are in accordance with recent work describing how children with lower stress levels show more highly developed social networks (high density of friendships) than children who suffer from chronic stress [63]. Moreover, our findings agree with previous investigations which also observed that social relationships were improved by cooperative play in children [53, 54] and that participation in a mindfulness-based prosocial training curriculum was able to promote self-regulation and prosocial behavior in young children [3, 6]. While recent studies have evaluated the peer relationships of children using social network analysis (e.g., [63–66]), to the best of our knowledge, few studies have been carried out to evaluate changes in social dynamics after applying an intervention.

Interestingly, the activities carried out in the present investigation seem to have helped decrease self-centeredness in children, enabling them to connect with others and develop empathic concern, thus promoting higher richness of social diversity. This ties in well with the enactive theory which proposes that cognition emerges from participation and emphasizes the key role of participatory sense-making experiences, in which interaction plays more than a contextual role as it can promote social cognition [43, 45, 47].

Previous investigations have shown that empathy, which involves cognitive and emotional understanding of others, is related to emotional regulation [67] and the identification of others' situations, that enable the emergence of prosocial attitudes [8, 20]. Other studies have shown that mindfulness-based practices can contribute to the regulation of emotions as well as attentional focus (e.g., [3, 6, 51, 68–70]).

The improvement of social relationships was accompanied by positive relational attitudes. For example, significant changes were observed during the reflective instance when children shared their appreciation of the experience and listened to others. We found that children were much more attentive to peers' verbal comments. In these perspective-taking instances children could become aware of peers' perceptions, feelings, and needs, in addition to the self-perception of emotional states during the activities. This cognitive-based awareness could have favored recognition of the consequences of their own actions and helped develop listening skills and the cultivation of empathy, as found in other studies [71]. In the same line, working on concern for others' well-being has been emphasized as an important contribution to children's healthy development and socialization [3, 72, 73].

One potential limitation of the current research could be associated with the fact that the control group continued with normal classes; however, a previous study demonstrated that children from a control group which carried out alternative activities did not show an improvement in the positive interactions between peers. Another potential limitation could be linked to the fact that we worked with one grade, since the intervention was conducted to promote positive social relationships in the group; thus, randomization was not possible. Future work carried out in other courses could provide further evidence confirming that the observed changes are not associated with a certain group but are related to the type of activities performed during this kind of intervention.

In sum, the current study shows that the practices and games conducted in the intervention enabled children to relate to others from a new perspective, improving social relationships between peers. Our findings illustrate the considerable behavioral plasticity and resilience of children. Using complex systems methodologies, the present investigation provides new evidence of social network plasticity, an important topic which, to our knowledge, has been little studied in children. The results indicate that positive changes in social network configuration can be promoted in educational settings. Given that these educational contexts offer a social environment that deeply affects children's development, our work highlights the beneficial effects of carrying out this kind of experience, which not only fosters prosocialness and empathic concern but also self-awareness, thus contributing to the enhancement of individual and social well-being.

5. Conclusions

The present study shows that a school intervention involving self-awareness and cooperative activities can enhance the diversity and quality of positive networks and reduce negative links between peers, diminishing antagonistic interactions. Since social interactions are crucial for a healthy development during childhood [63, 74–76], school interventions which improve social relationships are highly favorable. In this way, the implementation of these kinds of practices in educational settings might contribute to enhancing well-being in early life stages. The current work highlights the importance of fostering self-awareness and cooperative experiences at present, which might help increase social integration so much needed in education contexts. This investigation provides further evidence of the beneficial effects of prosocial attitudes in human wellness.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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Research Article

Socioemotional Dynamics of Emotion Regulation and Depressive Symptoms: A Person-Specific Network Approach

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Socioemotional processes engaged in daily life may afford and/or constrain individuals' emotion regulation in ways that affect psychological health. Recent findings from experience sampling studies suggest that persistence of negative emotions (emotion inertia), the strength of relations among an individual's negative emotions (density of the emotion network), and cycles of negative/aggressive interpersonal transactions are related to psychological health. Using multiple bursts of intensive experience sampling data obtained from 150 persons over one year, person-specific analysis, and impulse response analysis, this study quantifies the complex and interconnected socioemotional processes that surround individuals' daily social interactions and on-going regulation of negative emotion in terms of recovery time. We also examine how this measure of regulatory inefficiency is related to interindividual differences and intraindividual change in level of depressive symptoms. Individuals with longer recovery times had higher overall level of depressive symptoms. Also, during periods where recovery time of sadness was longer than usual, individuals' depressive symptoms were also higher than usual, particularly among individuals who experienced higher overall level of stressful life events. The findings and analysis highlight the utility of a person-specific network approach to study emotion regulation, how regulatory processes change over time, and potentially how planned changes in the configuration of individuals' systems may contribute to psychological health.

1. Introduction

Lifespan developmental theories view persons as complex dynamic systems, with feelings, thoughts, and actions that are interconnected and that change over time. Individual development is the product of numerous dynamic processes that span multiple levels of analysis, multiple domains of functioning, and multiple time-scales [1–3]. At their core, most developmental theories conceive individuals' development as the output of a complex dynamic system that reorganizes and changes as individuals transition between life phases and are affected by life events.

In line with basic tenets of developmental theory, conceptual work and empirical studies have elaborated the view that individuals' on-going socioemotional processes are a dynamic system wherein emotions and social behaviors interact to produce or influence psychological health and development [4–6]. Emotions *facilitate* social behaviors [7], and social interactions *regulate* emotions [8], and these system dynamics are associated with general psychological health and with depression [9–11]. More specifically, the cyclic cause-effect structures nested within interconnected networks of emotions and social behaviors may afford and/or constrain individuals' emotion regulation in ways that affect psychological health. This paper presents new empirical work examining how the dynamics of individuals' daily emotional and social experiences are related to both interindividual differences and intraindividual changes in depressive symptoms. By leveraging intensive experience sampling data and new time-series based network methods, we examine how inefficiency of socioemotional regulation processes is linked to individuals' experience of depressive symptoms.

1.1. Emotion Regulation, Depression, and Feedback Loops. Substantial evidence suggests that inefficient regulation of negative emotions puts individuals at risk for and is a marker of depression [12]. Consistent with identification of the persistence of negative mood as a core symptom of depression [13], multiple experience sampling studies illustrate how greater emotional inertia, the extent of carryover from moment to moment, of negative emotion (i.e., within-person autocorrelation) is associated with depression and psychological maladjustment [14, 15]. Expanding on these studies, researchers have begun examining the temporal dynamics of multiple emotions simultaneously. Taking advantage of the conceptual and methodological advantages of time-series based network methods [16], Pe and colleagues [17], for example, examined how the structure of relations among 11 negative and positive emotions was related to psychological health. They found that individuals with major depressive disorder had stronger temporal relations among emotions, greater density of the emotion network, especially greater density of the network of negative emotions, compared to controls (see also [18]). Interpretation focuses on how network density indicates the emotion system's resistance to change and presence of spirals of mutually reinforcing negative emotions. The underlying idea is that dense networks are likely to contain feedback loops in which any disruption in negative emotions will reverberate and persist, a form of inefficient emotion regulation [19]. In contrast, sparse networks are unlikely to contain feedback loops, so that any newly introduced negative emotion dissipates before influencing other parts of the network, a form of efficient emotion regulation.

Building on this work, we further expand the relevant network of variables to include aspects of both emotional and social experience. Theoretical models and empirical findings already highlight the variety of interpersonal mechanisms that may be contributing to maladaptive emotion regulation and risk for depression [20, 21]. For example, excessive seeking of reassurance [22], negative evaluation from friends [23], and excessive self-disclosure regardless of social context [6] have all been linked to depression. Such behaviors often *solicit* negative reactions from social partners, including domineering behavior, dismissiveness, or rejection [22, 24–27] that, when an individual has strong emotional reactivity to close relationships, can *cycle back* to produce more negative emotions [28]. Indeed, experience sampling studies show that social interactions characterized by less warm and more submissive behaviors are accompanied by more negative emotions [29, 30]. Particularly problematic configurations of emotional and social experiences involve feedback loops that perpetuate experience of negative emotions, for example, when negative emotions lead to maladaptive social behaviors and interpersonal interactions lead to negative emotions (e.g., a cycle of negative/aggressive interpersonal transactions [31, 32]). In sum, studies of daily life suggest links between interpersonal and emotional experiences, with the possibility that specific types of dynamics, namely, feedback loops, are associated with individuals' experience of depressive symptoms.

To illustrate more directly how feedback loops may contribute to regulation, network-based models of two hypothetical individuals' socioemotional dynamics are shown in Figure 1. In Individual A's network (Figure 1(a)), higher sadness leads to lower happiness (a temporal relation where sadness influences subsequent happiness at -0.6), lower happiness leads to lower social engagement (a temporal relation where happiness influences subsequent communal behavior at +0.6), and lower social engagement leads to higher sadness (a temporal relation where communal behavior influences subsequent sadness at -0.6). The overall effect of this cyclic structure is positive, as indicated by multiplication of the three temporal relations ($-0.6 * 0.6 * (-0.6) = 0.216$). Hence the three temporal relations together form a positive feedback loop, a structure that sustains changes in sadness. In contrast, in Individual B's network (Figure 1(b)), there is a negative feedback loop because social engagement is positively associated with sadness. The overall effect of this cyclic structure is negative ($-0.6 * 0.6 * 0.6 = -0.216$); hence the three temporal relations together form a negative feedback loop. Here, the structure of the relations facilitates regulation of sadness. The impact of the feedback loops can be examined mathematically using *impulse response analysis* ([33]; details introduced in the Method section). As shown in the accompanying temporal profile of sadness, Individual A recovers from an increase in sadness (sadness = 1.0 at $t = 1$) by $t = 18$ (Figure 1(c)). In contrast, Individual B recovers from an increase in sadness (sadness = 1.0 at $t = 1$) by $t = 15$ (Figure 1(d)). This comparison illustrates that the positive feedback loop extends the recovery time of sadness by approximately 20%, an inefficient emotion regulation process.

1.2. Experience Sampling, Person-Specific Networks, and Recovery Time. Identifying feedback loops is relatively straightforward in low-dimensional systems or through experimental manipulation of controllable systems [34]. The potential complexity, however, compounds as the systems become larger (more variables) and more complicated (more realistic). Study of high-dimensional, multivariate human systems can be facilitated by (a) collection of intensive experience sampling (time-series) data and a combination of methods that (b) identify the network structure from those empirical time-series, (c) characterize performance of the network (e.g., efficiency of emotion regulation) by impulse response analysis, and (d) describe interindividual and intraindividual differences in systems through regression-based modeling.

1.2.1. Intensive Experience Sampling. Technological advances in mobile computing provide an infrastructure that allows for unprecedented opportunity to obtain the temporally dense and comprehensive experience sampling needed for studying individuals as high-dimensional, multivariate dynamic systems [35]. Studies wherein individuals provide many reports on their emotions and interpersonal behaviors as they go about their daily lives are beginning to obtain the types of multivariate time-series data needed to identify and model the complex feedback loops involved in emotion regulation. Multiple time-scale or "measurement burst" study designs, wherein data are collected at both micro- and macrotimescales (hours and months; [36, 37]) provide new opportunities to observe how the moment-to-moment

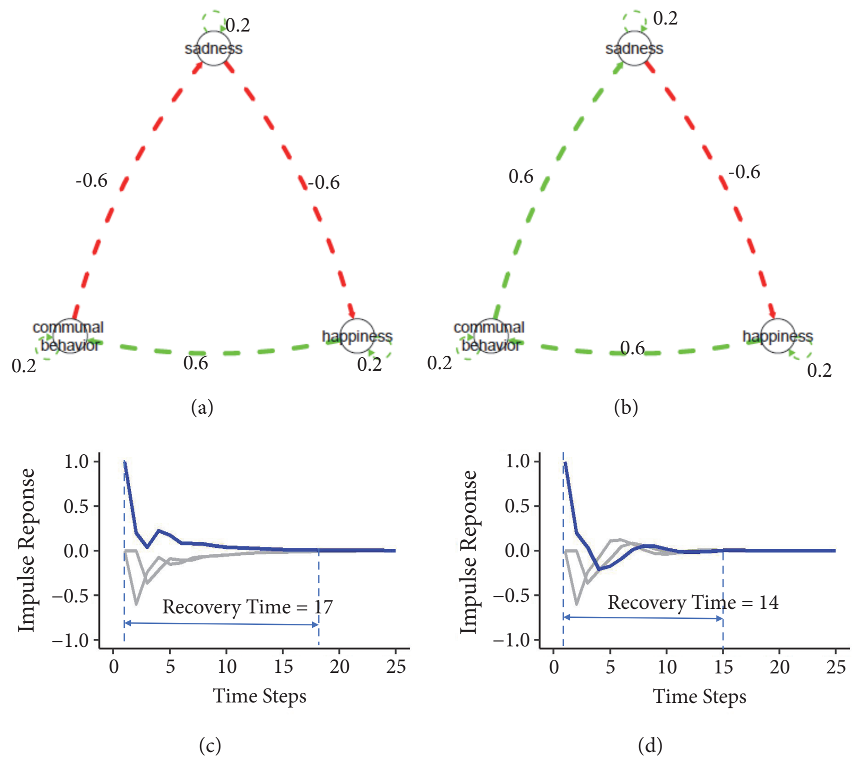


Figure 1: Conceptual example to illustrate effect of socioemotional dynamics on emotion regulation. (a) and (b) are two different networks, and edges (arrows) indicate significant temporal associations between nodes (circles). Red edges are negative associations, green edges are positive associations. Dashed edges are lagged effects. Edge width indicates strength of the temporal relation, whose weight is marked close to the edges. Both networks have density of 2.4. (c) and (d) are corresponding time profiles for the networks in (a) and (b), respectively.

processes governing short-term behavior (e.g., socioemotional dynamics) evolve over the long-term.

1.2.2. Modeling Socioemotional Process as a Person-Specific Network. The time series data collected in experience sampling studies facilitates use of network methods for studying within-person processes [16, 19]. In these models, the temporal relations among variables in the time series data are estimated by person-specific multivariate time-series methods and depicted as a network of paths between nodes [38]. For example, the intensive experience sampling data shown in Figure 2(a) was used to derive the network of relations shown in Figure 2(b). Each emotion and social behavior variable is represented as a node (labeled circles) in the network, and the statistical relations between each pair of variables is represented as an edge (arrows). Influences of variables on other variables are represented as directional paths that indicate how changes in one variable influence other variables subsequently. The directionality of edge indicates causal relations (e.g., the edge pointing from happiness to anger indicates that changes in happiness are likely to lead to changes in anger). The sign, strength, and temporal lag of the relations are indicated by color (green = positive, red = negative), line width (wider = stronger), and line-type (dashed = lag-1, solid = contemporaneous), respectively. Altogether the 13 nodes and connecting edges in the network shown in Figure 2(b) provide a model for how this specific individual's socioemotional system functioned during the 21-day period during which they provided the data.

1.2.3. Recovery Time as a Description of Individuals' Emotion Regulation. The person-specific network depicted in Figure 2(b) is notably larger and more complex than the networks depicted in Figure 1. While the network does provide better coverage of the socioemotional space (13 versus 3 variables), identification and interpretation of the embedded feedback loops are substantially more difficult. Often, the structure of larger networks is quantified using summary measures such as network-density and node-centrality (see [39]). However, because these metrics usually involve summing the absolute value of edges, they do not differentiate between positive (excitatory) or negative (inhibitory) feedback loops, i.e., loops that have opposite regulatory function (note that the networks in Figure 1 both have density = 2.4). More direct quantification of the emotion regulatory implications of the network structure can be obtained using *impulse response analysis* [33]. An "impulse" is given to a specific node and the behavior of the system observed through simulation over many time steps [40–42]. For example, in Figure 2(c), we see the behavior of the network shown in Figure 2(b) after an impulse is delivered to the sadness node. The impulse filters through connected nodes (due to the temporal relations) before returning to equilibrium. The *recovery time* depends on the existence and configuration of

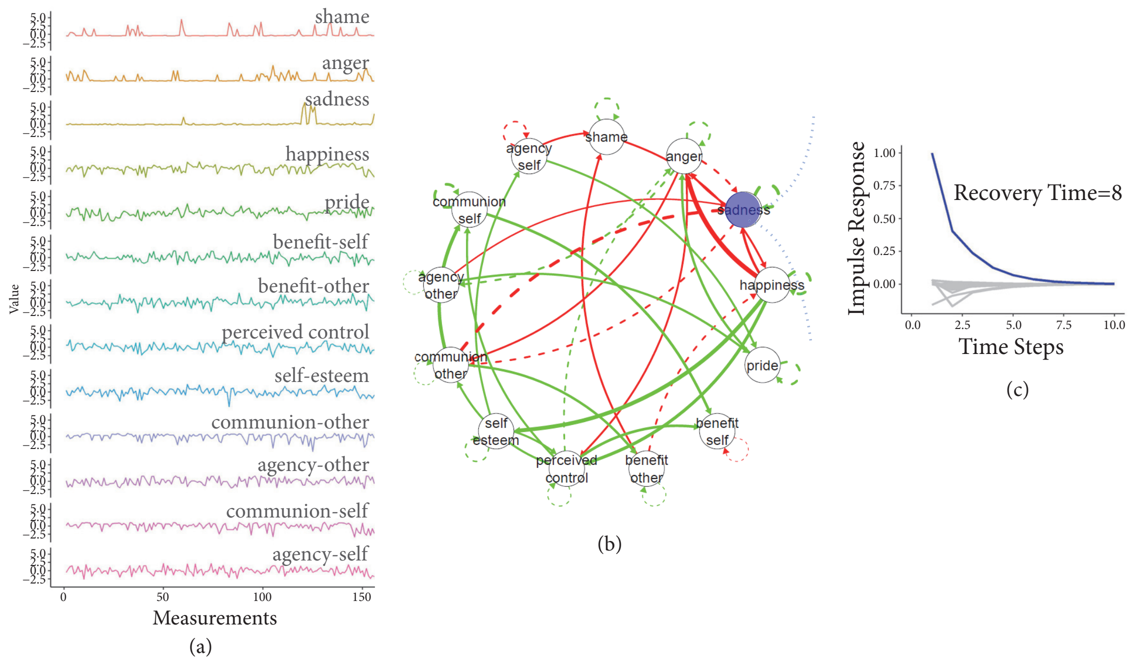


FIGURE 2: Illustration of the time-series, network graph, and impulse response analysis for one individual. (a) is the standardized time-series of 13 variables of one burst from one individual. (b) is the network graph of the temporal relations in the time-series from (a), obtained using uSEM. (c) is the time profile of the impulse response analysis of the network in (b) (sadness is represented by the blue line; the other twelve variables are represented by grey lines).

positive and/or negative loops within the network (see, e.g., [43–45]), with positive feedback loops extending recovery time and negative feedback loops shortening recovery time. This simulation approach provides new opportunities to measure the efficiency of individuals' emotion regulation.

1.3. The Present Study: Associations between Recovery Time and Depressive Symptoms. In this study we use multiple "bursts" of intensive experience sampling data obtained from 150 persons over one year, person-specific network analysis, and impulse response analysis methods to derive a new network metric, *recovery time*, to quantify emotion regulation efficiency and emphasize consideration of the complex and interconnected socioemotional processes surrounding day-to-day social interactions and regulation of emotions. We then examine how recovery time for sadness is related to interindividual differences and intraindividual change in the experience of depressive symptoms. We hypothesize that the network's efficiency to regulate sadness is related to level of depressive symptoms because persistent sadness is a prominent feature of depression [13]. Specifically, we expect that individuals with longer recovery time will experience more depressive symptoms (between-person association). During bursts where recovery times are longer than usual, the prototypical person will also experience more depressive symptoms than usual (within-person association).

Acknowledging that emotion regulation is related to and influenced by interpersonal behaviors (see [6] for review), we include as many variables as possible in the person-specific networks. Available data obtained in the context of the normal social interactions in daily lives include some negative emotions (sadness, anger, and ashamed), some positive emotions (happy, proud), interpersonal behaviors and perceptions (communion, agency), perceived benefits for self and other, perceived control, and self-esteem. Rather than specifying how each variable contributes to regulation of sadness, we explicitly take a holistic view and use the temporal relations among all these variables to derive how an individual's regulation of sadness is related to the experience of depressive symptoms. Given that change in depressive symptoms may also be related to individuals' immediate life context [46–48], we control for differences in stressful life events.

2. Method

Our analysis makes use of data from the Intraindividual Study of Affect, Health, and Interpersonal Behavior (iSAHIB), a multiple time-scale experience sampling study designed for articulation and study of process-oriented theory and methods [49]. An analysis tutorial is available in the supplementary material (available here), as well as at https://quantdev.ssri.psu.edu/tutorials.

2.1. Participants. The iSAHIB sample consists of 150 adults (50% women), recruited from The Pennsylvania State University and surrounding community and stratified by gender and age to cover the full adult life span. Participants ranged in age from 18 to 89 years (M_{Age} = 47.10, SD_{Age} = 18.76) and had obtained between 2 and 24 years of formal education (M_{Educ} = 16.36, SD_{Educ} = 3.90), with 91% self-identifying as Caucasian (4% African American, 1% Asian American, and 4% Mixed or

Other ethnicity). Most individuals identified as heterosexual (93%) with 6% identifying as bisexual/gay/lesbian. After participants were recruited, informed of the intensive nature of the assessments, and self-selected into the study, they began the assessment protocol. Over the course of a year, they provided extensive reports about their lives through a combination of web-based (completed during visits to the laboratory) and smartphone-based (completed multiple times per day during regular daily life) questionnaires.

Although the participants are drawn from the general community, they exhibit a range of maladjustment. Borderline personality disorder symptoms were measured using the Personality Assessment Inventory-Borderline Features Scale [50], a 24-item Likert-scale questionnaire, with items measured on a 1 to 4 Likert scale. Participants were prompted to "give your own opinion of yourself" on 4 dimensions, including affective instability, identity problems, negative relations, and self-harm. Item responses were summed to obtain a composite measure of disorder severity, which ranged from 27 to 72 (M_{PAIBFS} = 44.6, SD_{PAIBFS} = 10.0). Child abuse and trauma experiences were captured with the Child Abuse and Trauma Scale [51], a 14-item questionnaire, with items measured on a 1 to 5 Likert scale. Participants were promoted to "respond to the question in terms of the person or persons who had the primary responsibility for your upbringing as a child" on 4 dimensions, including physical, verbal, sexual, and emotional abuse. Item responses were summed to obtain a composite measure of the severity of child abuse and trauma, which ranged from 14 to 59 (M_{CATS} = 23.3, SD_{CATS} = 9.3). Interpersonal problems were measured using the Interpersonal Problems Circumplex [52], a 32-item questionnaire, with items measured on a 0 to 4 Likert scale. Participants were prompted to rate themselves on 8 dimensions, including domineering, vindictive, cold, socially avoidant, nonassertive, exploitable, overly nurturing, and intrusive. Item responses were summed to obtain a composite measure of the severity of interpersonal problems, which ranged from 6 to 73 (M_{IPCS} = 33.6, SD_{IPCS} = 15.7).

2.2. Experience Sampling Procedure. Participants completed three 21-day "measurement-bursts" spaced at approximately even intervals over one year. During each 21-day burst, individuals used a study-provided smartphone with a customized application to provide event-contingent reports of face-to-face social interactions that lasted longer than five minutes. Each interaction-level report included descriptions of when and where the interaction occurred, whom the interaction was with, how they and their partners behaved, and how they felt afterward. To facilitate compliance, the smartphones were programmed to chime a prompt if the participant did not provide a report for any two-hour span between 8 am and 8 pm. Data flow was monitored in real-time, a process that enabled the research staff to make periodic "check-in" calls that supported, motivated, and helped participants (e.g., solving technical problems) provide high-quality data. Over the entire study period, participants provided multivariate time-series with, on average, 427.4 observations (SD_T = 145.7, Range = 88 to 869) during 422 measurement burst periods (of a possible 450, because of some sample attrition). At the beginning and end of each burst, individuals visited the laboratory, received training or debriefing, picked-up or dropped-off smartphones, and completed demographic, health, personality, and other questionnaires. Participants were compensated $500 for completing the entire protocol.

2.3. Measures. The present analysis uses all available emotion and interpersonal variables in the experience sampling protocol to derive network representations of individuals as high-dimensional, multivariate dynamic systems and relates specific aspects of network function (recovery time following an impulse of sadness) to burst-level data on individuals' depressive symptoms and experience of life events.

2.3.1. Emotion and Interpersonal Behavior. After every social interaction (event-contingent sampling), participants were prompted with a series of items that they responded to using a 'touch-point continuum' (e.g., slider-type interface that allowed for continuous range between left anchor *"Not at All"* and right anchor *"Very Much"*) that was digitally coded on a 0 to 100 scale (numbers not visible to participants). After each social interaction, individuals reported on five emotions. Individuals' *shame* was measured using the item, "How ASHAMED do you feel right now?" ("*Not at all . . . Very much*"). Across all social interactions, individuals rated very low levels of *shame* (*M* = 6.45, *SD* = 9.42). Individuals' *anger* was measured using one item, "How ANGRY do you feel right now?" (*M* = 8.19, *SD* = 12.85). Individuals' *sadness* was measured using the item, "How SAD do you feel right now?" (*M* = 10.63, *SD* = 15.51). Individuals' *happiness* was measured using the item, "How HAPPY do you feel right now?" (*M* = 63.82, *SD* = 22.00). Individuals' *pride* was measured using the item, "How PROUD do you feel right now?" (*M* = 54.14, *SD* = 27.23).

Individuals also reported on a variety of interpersonal and intrapersonal factors. Social partners' interpersonal communion and agency [53] was measured by asking participants to "Rate how THE OTHER PERSON acted", and two sliders with end-point anchors of "Distant . . . Friendly" and "Submissive . . . Dominant" for *communion-other* (*M* = 80.44, *SD* = 15.96) and *agency-other* (*M* = 56.79, *SD* = 18.20), respectively. Parallel measurement of the participant's own interpersonal behavior, *communion-self* (*M* = 82.09, *SD* = 14.78) and *agency-self* (*M* = 55.08, *SD* = 17.23), was prompted by the item "Rate how YOU acted", and the same two sliders. Individuals' current impression of benefit for self (*benefit-self*) was measured by the item, "How useful was this interaction for YOU?" ("*Very costly . . . Very Beneficial*"; *M* = 64.11, *SD* = 20.46). In parallel, individuals' current impression of benefit for the person they just interacted with (*benefit-other*) was measured by the item, "How useful was this interaction for THE OTHER PERSON?" (*M* = 65.51, *SD* = 19.13). Individuals' *perceived control* was measured using the item, "I have control over the things happening to me right now." ("*Not at all... Very much*"; *M* = 70.81, *SD* = 21.67), and *self-esteem* with the item, "I have high self-esteem right now." (*M* = 67.09, *SD* = 23.77).

For illustration, one individual's multivariate, 13-dimensional time-series data from one burst are shown in

Figure 2(a). As can be seen, the value of each variable fluctuated from interaction to interaction across the course of study, some more than others, with some moving in synchrony (e.g., *anger* and *shame*, *cross-correlation* = 0.34), some moving in opposite directions (e.g., *anger* and *happiness*, *cross-correlation* = -0.22) and some with minimal interrelations (e.g., *agency-other* and *agency-self*, *cross-correlation* = -0.001). Notable are the length of this time-series ($T > 150$), the extent of intraindividual variability, the "stationarity" of the series (i.e., fluctuating rather than drifting up or down over time), and the level of synchrony among pairs of variables.

2.3.2. Depressive Symptoms and Life Events. Prior to each of the three bursts, individuals' recent experience of *depressive symptoms* was measured using the 20-item Center of Epidemiologic Studies Depression Scale (CESD; [48]). Participants were prompted with the stem, "How often have you felt this way during the past week?" followed by a list of symptoms (e.g., loss of appetite, restless sleep, feeling lonely, being happy). Each of these items required indication in 1 of 4 checkboxes labeled "*Rarely or none of the time (less than 1 day), Some or little of the time (1-2 days), Occasionally or moderate amount of time (3-4 days), Most or all of the time (5-7 days)*". Item responses on a 0 to 3 scale were summed to obtain a composite measure of the severity of depressive symptoms for each burst (M = 10.00, SD = 8.25). A CESD score of 16 is a recommended cut-off to screen for clinical depression [54]. In the current sample, the number of participants scoring ≥16 was 67 participants at burst 1, 57 participants at burst 2, and 47 participants at burst 3. In the context of a general community (versus a clinical) sample, we chose to operationalize depression dimensionally (level of depressive symptoms) rather than categorically (depressive disorder present/absent). Clinical psychology and psychiatry are moving toward dimensional models of psychopathology due to the limitations of categorical models of mental disorder [55]. It is common to employ dimensional measures of depressive symptoms in clinical research, including studies using the CESD (e.g., [56]) and studies examining associations among emotion networks and depressive symptoms (e.g., [18]). Dimensional models of depression are better predictors of functioning than categorical ones [57] and are part of a broader dimension of internalizing symptoms [58].

Given that burst-to-burst changes in depressive symptoms may be related to individuals' immediate life context [46–48], we controlled for differences in recent life events. Individuals' recent life experiences were probed using 12 items adapted from *life events* scales [59, 60]. Participants were prompted with the stem, "Since the last time we saw you, [or at the first visit, "In the last 6 months,"] did you experience a change in the following and, if so, how much did it affect you?" followed by a list that included significant life events (e.g., change in relationship status, loss of loved one, hospitalization). Each of these items required participants to check 1 of 5 checkboxes labeled "*Did not experience, Not affected, A little bit, Somewhat, A lot*". Responses coded on a 0 to 4 scale were summed to obtain a composite measure of the impact of recent life events for everyone at each burst (M = 6.18, SD = 6.08).

2.4. Data Preparation and Analysis. There were three stages in the data analysis. In the first stage, uSEM [61] was used to construct person-specific networks that describe the configuration and temporal relations underlying each person's 13-dimensional multivariate time-series data at each burst (422 networks). In the second stage, the behavior of these networks was quantified using impulse response analysis [33] to obtain network-specific recovery times for sadness, a measure of emotion regulation. In the third stage, we used multilevel models to examine how recovery time was related to interindividual differences and intraindividual changes in depressive symptoms, controlling for differences and changes in life events.

2.4.1. Data Preparation. Before analysis, the data were examined for suitability of application. The general guiding principle for application of uSEM is that the multivariate time-series data can be treated as weakly stationary (with means and variance-covariance structure that is constant over time; see details on preprocessing in [7]). Visual inspection of each individual's data and testing of polynomial trends (see [62]) suggested that the data were reasonably stationary (an exemplar participant's time-series is shown in Figure 2(a)). To focus analysis on intraindividual *regulation dynamics*, the 13-variable time-series for each burst for each person were standardized into a z-metric ($M = 0$, $SD = 1$), thereby effectively removing burst-to-burst and person-level differences in level and variance (see, e.g., [63]).

2.4.2. Construction of Networks. Individual data from each burst were then modeled as a multinode dynamic network using a unified Structural Equation Model (uSEM, [61]). In brief, the multivariate observed time-series $y(t)$ is modeled as the output of a latent variable time series $\eta(t)$,

$$y(t) = \boldsymbol{\Lambda}\eta(t) + \varepsilon(t) \tag{1}$$

where $\boldsymbol{\Lambda}$ is a factor loading matrix and $\varepsilon(t)$ is a time-series of residuals with variance-covariance structure given by a matrix $\boldsymbol{\Theta}$, that is assumed diagonal. The temporal relations among the set of latent constructs in $\eta(t)$ (the circles in Figure 2(b)) are then modeled as

$$\eta(t) = \boldsymbol{A}\eta(t) + \boldsymbol{\Phi}_1\eta(t-1) + \zeta(t) \tag{2}$$

where $\eta(t-1)$ is a vector of the lag-1 version of the multivariate latent time-series; $\boldsymbol{A}$ is a matrix of regression parameters that describe the contemporaneous relations among the latent variables (solid arrows in Figure 2(b)), $\boldsymbol{\Phi}_1$ is a matrix of regression parameters that describe the lag-1 relations (auto- and cross-regressions) among the latent variables (dashed arrows in Figure 2(b)), and $\zeta(t)$ is a multivariate "shock" or input time series. Together, the contemporaneous relations in $\boldsymbol{A}$ and auto- and cross-regressive relations in $\boldsymbol{\Phi}_1$ indicate the causal influences among variables through which exogenous input is processed and diffused (i.e., dynamic regulation). At the practical level, the uSEM model is estimated using an iterative search process wherein a series of models are constructed and tested for improvements in fit. At each step, Lagrange Multiplier tests (modification indices; Sörbom, 1989) are used to select the path that facilitates maximum improvement in fit. This element is then freed, the model reestimated, and a new set of modification indices calculated, iteratively adding paths until further addition does not significantly improve model fit. The model expansion was constrained so that only $\boldsymbol{A}$ and $\boldsymbol{\Phi}_1$ blocks of the model parameter matrix were freed, thus keeping the time-series structure of the model intact. Bidirectional paths in the contemporaneous relations are avoided by including all potential autoregression relations in the initial model and by deeming the opposite path unavailable when any given element in $\boldsymbol{A}$ was freed. In experience sampling study designs being used to collect multivariate, intensive longitudinal data, the item pool has often been optimized to minimize participant burden. In cases where each latent construct has been measured by only one item, the factor loading matrix $\boldsymbol{\Lambda}$ is configured as an identity matrix $\boldsymbol{I}$, and all elements of $\boldsymbol{\Theta}$, the variance-covariance matrix of $\boldsymbol{\varepsilon}_{t-1}$, and $\boldsymbol{\varepsilon}_t$ are fixed = 0.

Person-specific models for each burst were estimated by adapting R code from the Group Iterative Multiple Model Estimation package (GIMME; [64]). The adaptation was mainly to ensure the model fitting procedure will produce an interpretable result, including allowing no more than one direction of contemporaneous relation being fitted between two variables, and setting the autoregression to be freed in the initial iteration in the fitting procedure. Once the person-specific models for each burst were obtained, $\boldsymbol{\Phi}_1$ and $\boldsymbol{A}$ matrices were extracted and drawn as network graphs using the qgraph package [65]. Conceptually, the resulting network describes how behavior is organized and proceeds at the micro time-scale. A sample network is shown in Figure 2(b), where, for example, sadness was predictive of lower other's communal behavior at the next observation, and other's communal behavior was also predicting of lower sadness at the next observation (red dashed line from other's communion to sadness and the opposite direction in Figure 2(b)). These two edges together form a positive feedback loop between sadness and other's communion.

2.4.3. Impulse Response Analysis and Recovery Time. Each of the 422 networks (150 persons x 3 bursts, minus some attrition) was then summarized with respect to the *recovery time* of sadness, quantified as the number of time steps until the level of sadness returns to near equilibrium (e.g., within 0.01 of the asymptote) after a hypothetical perturbation. Formally, the impulse response simulation model is constructed by converting the uSEM into a vector autoregression model and doing one step ahead forecasting (see (3); [33, 61, 66]).

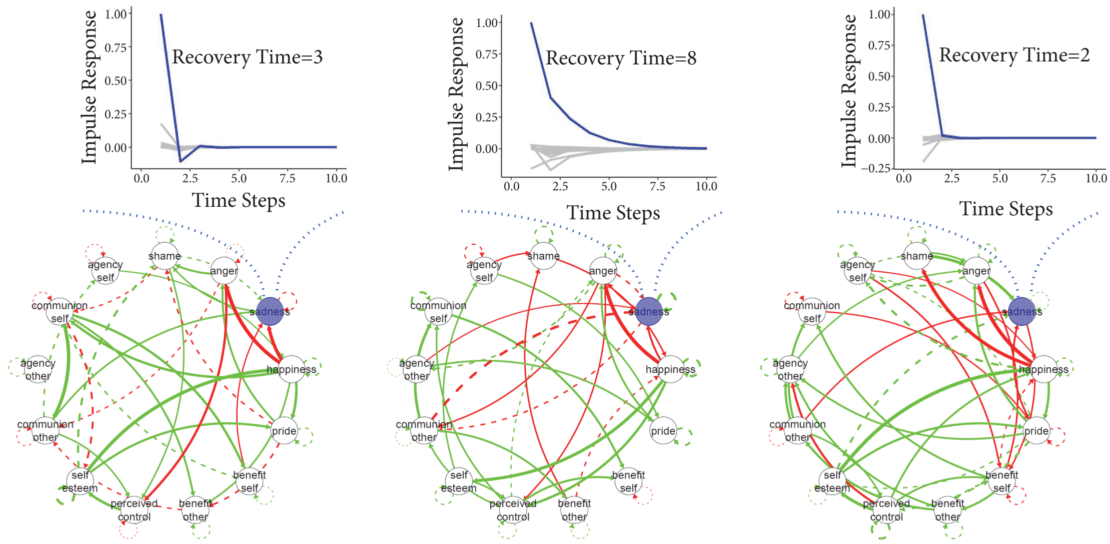
$$\eta(t) = (\boldsymbol{I} - \boldsymbol{A})^{-1} \boldsymbol{\Phi}_1 \eta(t-1) + (\boldsymbol{I} - \boldsymbol{A})^{-1} \zeta(t) \tag{3}$$

In our case, the system is set in motion by sending an initial impulse to the sadness node (sadness = 1.0 at $t = 1$) and computing how the system evolves over 150 time steps (to guarantee a sufficient length for all nodes to return to equilibrium). The time profile obtained from the impulse response analysis of the network in Figure 2(b) is shown in Figure 2(c). *Recovery time*, defined as time to return within ±0.01 of equilibrium, was then derived through a backward search to accommodate oscillation in the time profiles. Specifically, we searched *backward* from the end of the time profile, to identify the time-step, denoted as k, where the level of a specific variable was *first* outside the ±0.01 boundary. Recovery time was then quantified for the sadness node as k, the number of time steps from perturbation to equilibrium. Within-person differences across bursts are illustrated in Figure 3. The recovery time of sadness for this individual changed across bursts, starting at $k_1 = 3$ in the first burst, increasing to a $k_2 = 8$ in the second burst, before returning to $k_3 = 2$. Because the distribution of recovery times is skewed (cannot go below zero), scores were log-transformed before being used in the third stage of analysis.

2.4.4. Associations between Recovery Time and Depressive Symptoms. Because the equilibrium represents the average value of sadness and the normal sadness level is rather low ($M = 10.63$, $SD = 15.51$), disruption of sadness from the equilibrium is most likely to result in an increased level of sadness, which is undesirable subjectively. Thus, positive feedback loops around sadness which sustain this disruption are also undesirable. This informed our hypothesis that emotion regulation inefficiency of sadness embedded in individuals' socioemotional networks is related to higher (individual differences in) and increased (intraindividual changes in) *depressive symptoms* (ICC = 0.65, skewness = 1.25), controlling for *life events*. Making use of and accommodating the nested nature of the multiple-burst longitudinal data (422 bursts nested within 150 persons), hypotheses were examined within a multilevel modeling framework [67]. Following usual practice, the predictor variables were split into time-invariant (person-level means; $OverallLifeEvents_i$, $OverallRecoveryTime_i$) and time-varying (burst-to-burst deviations, $BurstLifeEvents_{ib}$, and $BurstRecoveryTime_{ib}$) components. Relations among the extended set of variables were then examined using 2-level models of the form

$$\begin{aligned} Depressive_{ib} = {} & \beta_{0i} + \beta_{1i} BurstLogRecoveryTime_{ib} \\ & + \beta_{2i} BurstLifeEvents_{ib} \\ & + \beta_{3i} BurstLogRecoveryTime_{ib} \\ & * BurstLifeEvents_{ib} + e_{ib} \end{aligned} \tag{4}$$

where the repeated measures of depressive symptoms for individual i at burst b, $Depressive_{ib}$, are modeled as a function of person-specific intercepts, β_{0i}, that indicate baseline level of depressive symptoms; person-specific coefficients, β_{1i} and β_{2i}, that indicate the extent of within-person associations between burst-specific log recovery time or life events, respectively, and depressive symptoms; and coefficient, β_{3i}, that capture how life events moderate the within-person association between burst-specific log recovery time and depressive symptoms. Person-specific coefficients were



(a) (b) (c)

Figure 3: Illustration of change in network structure and recovery time across the three bursts ((a), (b), and (c), respectively) for one individual. Corresponding recovery times were $k_1 = 3$, $k_2 = 8$, and $k_3 = 2$, respectively.

simultaneously modeled as a function of person-level predictors

$$\beta_{0i} = \gamma_{00} + \gamma_{01} OverallLogRecoveryTime_i + \gamma_{02} OverallLifeEvents_i + u_{0i} \quad (5)$$

$$\beta_{1i} = \gamma_{10} + \gamma_{11} OverallLogRecoveryTime_i + \gamma_{12} OverallLifeEvents_i + u_{1i} \quad (6)$$

$$\beta_{2i} = \gamma_{20} + \gamma_{21} OverallLogRecoveryTime_i + \gamma_{22} OverallLifeEvents_i + u_{2i} \quad (7)$$

$$\beta_{3i} = \gamma_{30} \quad (8)$$

where γ_{00} to γ_{30} are sample-level parameters and u_{0i} to u_{2i} are residual unexplained between-person differences that are assumed multivariate normal with variances $\sigma^2_{u_{0i}}$, $\sigma^2_{u_{1i}}$, and $\sigma^2_{u_{2i}}$ and covariances $\sigma_{u_{0i},u_{1i}}$, $\sigma_{u_{0i},u_{2i}}$, and $\sigma_{u_{1i},u_{2i}}$. The model was fit to the data using the nlme package in R [68], with incomplete data (0.2%) treated as missing at random. Person-level predictors were sample-centered to facilitate interpretation of model parameters as representing effects for the prototypical person (as described by the average demographics above). All possible interactions were tested, but, to maintain parsimony in the presentation of the final models, iteratively trimmed to remove those that were nonsignificant ($\alpha = 0.05$) and not directly related to the hypotheses (always retaining the component main effects and lower-order interactions). Also, a variety of random effects structures were tested, with the different configurations having little influence on the fixed effects parameters or interpretations (i.e., no changes in significant effects). For parsimony, we present and interpret only the final model, which included random effects u_{0i} and u_{2i}.

3. Results

3.1. Socioemotional Networks and Recovery Time. Person-specific socioemotional networks were derived from the 13-variate time-series obtained from each person during each 21-day burst of measurement using uSEM. Of the total 422 network models, 411 fit the data well, as indicated by at least three of the following fit criteria: RMSEAs ≤ 0.08, SRMRs ≤ 0.08, CFIs ≥ 0.95, NNFI ≥ 0.95 (see Beltz et al., 2013). Models from 11 bursts with relatively short time-series (T = 31 to 62, compared to $T_{average}$ = 145.7) did not fit well and were set aside. The lagged and contemporaneous relations among variables were extracted and used in an impulse response analysis to calculate person- and burst-specific recovery times for sadness. Recovery time, interpreted as a measure of (in)efficiency of emotion regulation, ranged from 1 to 57 ($M_{sad.RT} = 4.63$, $SD_{sad.RT} = 5.32$).

3.2. Associations between Recovery Time and Depressive Symptoms. Results from the multilevel model examining between-person and within-person associations between log recovery time of *sadness* and level of depressive symptoms are shown in Table 1. Level of depressive symptoms for a prototypical individual in an average burst was 9.84 ($\gamma_{00} = 9.84$, $p < 0.001$) on a 0 to 60 scale. As expected, between-person differences in log recovery time of sadness were associated with differences in level of depressive symptoms, with, as shown in Figure 4(a), longer recovery times linked to higher level of depressive symptoms ($\gamma_{01} = 2.29$, $p = 0.031$), even after controlling for the significant effect of stressful life events ($\gamma_{02} = 0.70$, $p < 0.001$). The within-person association was

Table 1: Results from the final model examining association between depressive symptoms and log recovery time of sadness, after controlling for life events in each model.

Parameters	*Estimates (SE/CI)*		*Estimates (SE/CI)*		*Estimates (SE/CI)*	
Fixed Effects						
Intercept, γ_{00}	9.84*	(0.49)	9.42*	(0.47)	9.71*	(0.39)
LE_i, γ_{02}	0.70*	(0.10)	0.68*	(0.10)	0.43*	(0.09)
LE_{bi}, γ_{20}	0.18*	(0.07)	0.17*	(0.08)	0.18*	(0.07)
$LogRT_i$, γ_{01}	2.29*	(1.06)	1.96*	(1.05)	0.93	(0.91)
$LogRT_{bi}$, γ_{10}	1.26*	(0.50)	1.35*	(0.51)	1.16*	(0.50)
$LE_i \times LogRT_{bi}$, γ_{12}	0.32*	(0.11)	0.33*	(0.12)	0.31*	(0.11)
Age	-	-	-0.02	(0.03)	-	-
Gender	-	-	-0.58	(0.97)	-	-
Education (in years)	-	-	-0.23	(0.12)	-	-
PAIBFS	-	-	-	-	0.24*	(0.05)
CATS	-	-	-	-	0.03	(0.05)
IPCS	-	-	-	-	0.14*	(0.03)
Random Effects						
Variance Residual, $\sigma^2_{e_{ib}}$	19.17	(15.85, 23.19)	19.06	(15.70, 23.15)	18.93	(15.64, 22.91)
Variance Intercept, $\sigma^2_{u_{0i}}$	27.61	(20.41, 37.35)	22.47	(16.14, 31.28)	14.12	(9.75, 20.44)
Variance LE_{bi}, $\sigma^2_{u_{2i}}$	0.11	(0.04, 0.30)	0.12	(0.04, 0.31)	0.10	(0.03, 0.29)
Covariance intercept, LE_{bi}, $\sigma_{u_{0i},u_{2i}}$	0.75	(-0.07, 2.55)	0.67	(-0.08, 2.33)	0.29	(-0.18, 1.63)
-2Log-Likelihood	1315.14		1216.14		1242.47	

Note. N = 411 repeated measures nested within 150 persons. SE = standard error for fixed effects. CI = 95% confidence interval for random effects. $*p < 0.05$, LE = life events, $LogRT$ = log recovery time, PAIBFS = Personality Assessment Inventory-Borderline Features Scale, CATS = Child Abuse and Trauma Scale, and IPCS = Interpersonal Problem Circumplex Scale.

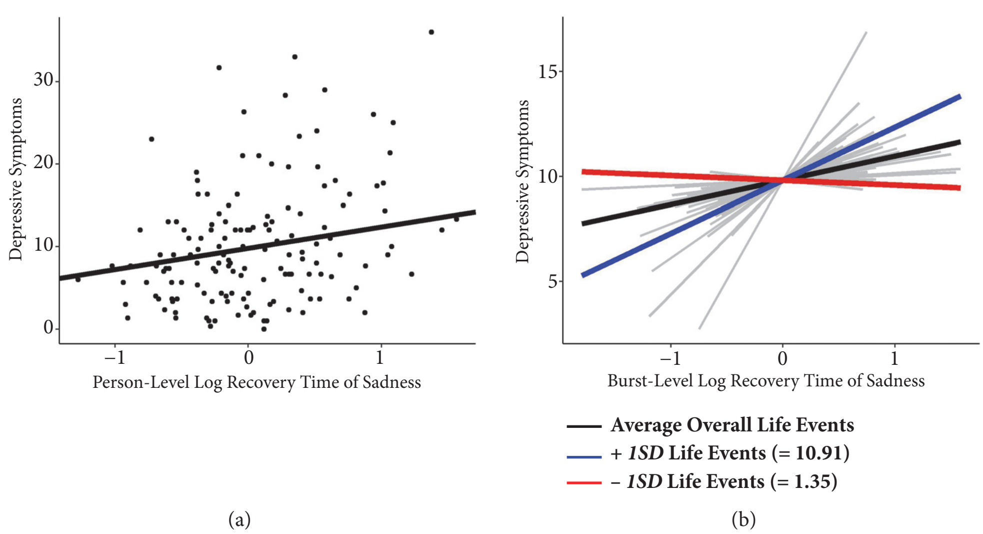


Figure 4: Model implied associations between log recovery time of sadness and depressive symptoms (CESD). (a) shows the between-person association: individuals with longer recovery time have higher level of depressive symptoms. (b) shows the prototypical within-person association (black line), the extent of between-person differences in the within-person association (gray lines), and how the within-person association was moderated by level of life events. For an individual with low life events (-1 *SD*, red line) there was no within-person association between recovery time and depressive symptoms, while for an individual with high life events (+1 *SD*, blue line), burst increases in recovery time were accompanied by more depressive symptoms.

also significant. During a burst where log recovery time of sadness was longer than usual, the prototypical person had a higher level of depressive symptoms (γ_{10} = 1.26, p = 0.013). However, this association was moderated by individuals' overall exposure to life events (γ_{12} = 0.32, p = 0.005). As shown in Figure 4(b), for an individual with high (+1 *SD*; blue line) exposure to life events, within-person changes in recovery time for sadness were strongly linked to depressive symptoms (implied within-person association β_{1i} = 2.80, 95% CI = [0.22, 5.01]), while for an individual with low

(-1*SD*; red line) exposure to life events, within-person changes in recovery time for sadness were not linked to depressive symptoms (implied within-person association β_{1i} = -0.28, 95% CI = [-2.86, 2.05]). Post hoc probing using the Johnson-Neyman method ([69]; implemented using the probemod package in R; [70]) indicated a significant within-person link between recovery time and depressive symptoms when level of (sample-centered) overall life-events was greater than 2.49.

Post hoc analysis controlling for age, gender, and education (in years) found the same pattern of results. The within-person association between log recovery time and depressive symptoms was significant (γ_{10} = 1.35, p = 0.009), while the between-person association became marginally significant (γ_{01} = 1.96, p = 0.065). Additionally, a separate post hoc analysis controlled for scores on the Borderline Features, Child Abuse and Trauma, and Interpersonal Problem Circumplex scales. The within-person association between log recovery time and depressive symptoms was significant (γ_{10} = 1.16, p = 0.02), while the between-person association became nonsignificant, but the direction of the association held (γ_{01} = 0.93, p = 0.30).

The autoregression of sadness of course plays a substantial role in recovery time of sadness. Thus, to check whether the results were only driven by a single variable rather than the feedback loops embedded in the larger network, we reran the impulse response analysis with the autoregression of sadness set to zero and calculated the recovery times again. Between-person differences in this log recovery time were no longer associated with depressive symptoms (γ_{01} = 1.14, p = 0.31), but the within-person association remained robust. In bursts where this log recovery time was longer, depressive symptoms were higher (γ_{10} = 1.22, p = 0.01), highlighting the effect of temporal relations aside from the autoregression (emotional inertia) of sadness.

4. Discussion

This paper examined emotion regulation from a within-person, process-oriented, and network perspective. Data obtained across multiple "bursts" of intensive experience sampling data over one year were used to construct person-specific networks that described the complex and interconnected socioemotional processes that surround individuals' day-to-day social interactions and on-going regulation of negative emotion. Impulse response analysis was used to describe and quantify the efficiency of individuals' regulation in terms of *recovery time*, and multilevel models were used to examine how recovery time was associated with between-person differences and within-person change in individuals' experience of depressive symptoms.

Working from basic principles, individuals were viewed as holistic interactive dynamic systems with a broad range of emotions and interpersonal behaviors that influence how they regulate negative emotions. We found that the behavior of the person-specific networks, in particular the recovery time of the illustrative negative emotion (sadness), was related to both between-person differences and within-person changes in depressive symptoms. In line with hypotheses, individuals with longer recovery times had higher overall level of depressive symptoms, even after controlling for recent life events. Also, during periods where recovery time of sadness was longer than usual, depressive symptoms were also higher than usual, particularly among individuals who experienced a higher overall level of life events. These results indicated both between-person and within-person links between regulatory inefficiency and depressive symptoms.

4.1. Person-Specific Networks, Emotion Regulation, and Depressive Symptoms. In line with prior work [17, 18, 71], we found evidence that emotional experiences in daily life are temporally related to each other (e.g., sadness, happiness) and to interpersonal behaviors (communion, agency). Distinct from prior studies using a multilevel modeling approach, the person-specific analysis approach allowed idiosyncratic temporal relations between any of the two nodes without constraining it to a sample-level mean. In the same way that multilevel models allow for interindividual differences in the relations among 2 or 3 variables, the person-specific network approach allows for heterogeneity in the structure of relations among many variables. Indeed, of the 411 networks we obtained, none were identical. Each individual and each burst provided a unique configuration of temporal relations, and this provided for examination of both interindividual differences and intraindividual changes in the socioemotional (network) dynamics.

Viewed as holistic representations of individual functioning, all 411 socioemotional network configurations were evaluated with respect to how well that configuration facilitated regulation of low arousal negative emotion, specifically, recovery time of sadness. Generally, regulatory processes, including those involved in emotion regulation, are engaged to bring a system back to equilibrium [15]. In prior work, efficiency to return to equilibrium has been examined through analysis of univariate time-series data. Specifically, the extent of autocorrelation or autoregression, emotion inertia, is quantified using experience sampling of single emotions and interpreted as an indicator of emotion dysregulation [14, 15]. The present study, along with other recent work [17], expands the investigation of emotion inertia and regulation by explicitly acknowledging that other aspects of daily life (e.g., interpersonal relations, control, self-esteem) can afford or constrain emotion regulation.

The between-person findings that individuals with longer recovery times for sadness had higher overall level of depressive symptoms confirms the interpretation of the recovery time metric as a measure of regulatory (in)efficiency and aligns with prior work demonstrating the relation between depression (or other psychological maladjustment) and inefficient regulation of negative emotions, and emotion inertia [12, 14, 15]. The interpretation is further bolstered by the within-person findings. Indeed, during periods where recovery time of sadness was longer than usual, depressive symptoms were also higher than usual. This is a new finding, facilitated by a multiple burst study design that provides for a more direct test of the within-person links between emotion (dys)regulation and depressive symptoms that has not been available in prior (single-burst or cross-sectional study) studies. Interestingly, after controlling for between-person differences in demographic variables as well as broad maladjustment scales, the within-person association between recovery time of sadness and depressive symptoms remains robust, indicating the within-person association deserves more consideration for future examination.

Importantly, this within-person association was moderated by overall level of life events. The fact that the link between regulatory inefficiency (as indicated by longer recovery time) and depressive symptoms was especially strong among individuals who experienced multiple, impactful life events suggests that the within-person links may be easier to observe when individuals are under duress, for example, in a "testing-the-limits" context (see [72]). To illustrate, consider the diagnosis of heart disease. Individuals are typically subjected to an exercise "stress test" wherein their cardiovascular reactivity and regulation is observed as their bodies are pushed towards their physiological limits (e.g., running on a treadmill). The general idea is to produce a situation where dysfunctionality can be more easily observed. Differences in cardiovascular function are not so apparent when individuals are resting or going about their daily lives. Under "stress" conditions, however, differences in functionality become clear and can be diagnosed and subsequently treated. Our moderation results suggest that "stress test" paradigms may also be useful in the study of emotion regulation in daily life. While it may require monitoring individuals for long durations, identification of natural experiments wherein individuals' adaptive capacities are being pushed to their limits should provide further opportunity to observe differences in emotion regulation.

4.2. Impulse Response Analysis and Person-Specific Intervention. The moderation result also highlights opportunity to use impulse response analysis in studies of intervention. The results of this study suggest that the combination of intensive experience sampling data, network methods, and impulse response analysis could inform the design and deployment of person-specific prevention or intervention [16, 73]. First, based on the information presented in the network, clinicians can discover maladaptive feedback loops and design a targeted treatment plan. For example, consider a case where, after a few weeks of monitoring, the clinician finds that their patient's socioemotional network contains a feedback loop wherein sadness leads to distant, unfriendly behavior (low communion), which in turn leads to more sadness. This configuration implies that persistence of negative mood might be alleviated through some social skills training, thus breaking the link between sadness and withdrawn, quarrelsome social behavior. Clinicians might also test or demonstrate the probable effect of a particular treatment plan by using impulse response analysis to simulate how different network constructions (current versus ideal) lead to different recovery times. For patient networks that contain multiple maladaptive feedback loops, impulse response analysis could be used to compare potential efficiency of different treatment plans. Of course, experience sampling data collected prior to, during, and after treatment would be especially useful for evaluating, if indeed, the network configuration changed in ways that facilitate functionality and health.

4.3. Limitations and Outlook. The results of this study must be interpreted with respect to some limitations in design and implementation. First, although stratified by age and gender, the sample of persons who provided data were somewhat homogenous. This study was based on a convenience sample that lived in or near a university town and consisted of individuals who were willing to participate in an intensive experience sampling protocol. Before generalizing to the larger population, it will be particularly useful to engage with other populations. Clinical populations, very old persons, or individuals who recently experienced particular types of life events (trauma), for example, may allow for more detailed study of network structure and regulation processes that are under duress. Since our sample had a homogeneous demographic profile (e.g., greater than 90% white, cisgender, and heterosexual), and given differences in depression rates among marginalized populations, it is important to verify these results in more diverse and/or special populations.

The study design used here followed persons intensively during three 21-day periods over one year, with each burst of measurement producing multivariate time-series of about 150 observations, a length that facilitated construction of 13-variable networks. Even so, the number of measurements available did not allow us to study intraindividual change in person-specific network structure within-burst. More dense sampling and/or longer time-series would provide possibilities to segment each time-series into multiple windows and either study how the network changes over shorter time-scales or obtain estimates of the reliability of the recovery time estimates (see, e.g., [74]). This will also be an opportunity to probe deeper into the relation of specific pairs of nodes (e.g., synchronization) and characteristics of a specific node (e.g., recovery time). Our hope is that as new technologies (e.g., wearable sensors) begin delivering more intensive and longer data streams, the opportunities to model more nuanced intraindividual change in network behavior will expand.

The data used here come from a multidisciplinary study that was designed around a select set of substantive domains and sampling procedures. Acknowledging that many actions, thoughts, and feelings are involved in the ongoing emotion regulation processes individuals engage in throughout daily life, we constructed the person-specific networks using 13 continuous-value variables assessed in an experience sampling questionnaire. While this set of variables matched our intent to model individuals as high-dimensional, multivariate dynamic systems, future studies might be either more selective or more inclusive in determining which variables to assess repeatedly and include as part of the dynamic system. More focused networks might be constructed using only emotions. Broader networks might also look to include a broader range of self-perceptions (e.g., self-worth) and cognitions (e.g., perseveration).

As in other work where network methods are being applied to experience sampling data [71, 75, 76], our analysis made use of a three-stage procedure. There are, of course, some risks in using the output from one analysis as input for the next analysis because the uncertainties present in earlier analyses are ignored in subsequent analysis. Generally, it would be better to estimate all the models simultaneously in a single model. To our knowledge, however, this is not yet possible. Therefore, the results should still be interpreted cautiously and conservatively.

We chose to perturb sadness and characterized the impulse response curve by recovery time because persistent sad mood is associated with depression. There could be other ways to perturb the system [77] and alternative characterizations of the impulse response analysis (area under the impulse response analysis curve; [78]). Future research could further examine various aspects of system behaviors when different nodes are perturbed (e.g., a node of social behavior).

4.4. Conclusion. Building upon previous work examining emotion regulation process with network approaches, this paper merged intensive experience sampling data and time-series based network methods to construct person-specific socioemotional networks. The evidence of interconnected networks showed that emotions and social behaviors are indeed working together interaction by interaction. Using recovery time to quantify regulatory efficiency of the socioemotional network, we provide further empirical evidence that the regulatory efficiency of the socioemotional dynamics is associated with depressive symptoms. The evidence of this association showed that the interconnected newtork of emotions and social behaviors are indeed contributing to emotion regulation.

Data Availability

The R code to conduct analytical steps (e.g., uSEM model fitting, impulse response analysis, network visualization) and the visualization of all person-specific networks used to support the findings of this study are included within the supplementary information file(s).

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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Supplementary Materials

There are two files in the Supplementary material. The "tutorial" documents the R code to conduct analytical steps (e.g., uSEM model fitting, impulse response analysis, network visualization) and the "411 networks merged file" consists of visualization of all person-specific networks. *(Supplementary Materials)*

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Research Article

Developmentally Changing Attractor Dynamics of Manual Actions with Objects in Late Infancy

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Human infants interact with the environment through a growing and changing body and their manual actions provide new opportunities for exploration and learning. In the current study, a dynamical systems approach was used to quantify and characterize the early motor development of limb effectors during bouts of manual activity. Many contemporary theories of motor development emphasize sources of order in movement over developmental time. However, little is known about the dynamics of manual actions during the first two years of life, a period of development with dramatic anatomical changes resulting in new opportunities for action. Here, we introduce a novel analytical protocol for estimating properties of attractor regions using motion capture. We apply this new analysis to a longitudinal corpus of manual actions during sessions of toy play across the first two years of life. Our results suggest that the size of attractor regions for manual actions increases across development and that infants spend more time inside the attractor region of their movements during bouts of manual actions with objects. The sources of order in manual actions are discussed in terms of changing attractor dynamics across development.

1. Introduction

Infants' emerging ability to manually interact with objects creates new possibilities for exploration and learning [1–3]. Manual skills develop incrementally: immature infants swat and bat at objects before becoming increasingly coordinated and flexible with their hands in the second year of life [4–20]. Manual actions, such as reaching and holding an object, require the dynamic coordination of the entire musculoskeletal system and are shaped by the demands of the task being performed. During development, this poses a considerable challenge: as their musculoskeletal system grows, the infant must develop and adjust their motor skills to a constantly changing body.

Prior research has examined the development of motor skills in infants [8, 11, 21–26], children [27–29], and adults [30–32]. Many of these studies observed that the beginning of learning a motor skill is characterized by the actor limiting the range of specific joints, thereby eliminating redundant degrees of freedom. Such behavior results in a limited range of movement patterns and a consistent behavioral outcome. Once proficiency is achieved, this restriction in the movement's degrees of freedom is released. Although this idea has been systematically studied in new skill development in adults and is used as the theoretical framework to interpret findings in motor development, there has been limited direct study across development [33], largely due to methodological limitations.

The human motor system—from the brain to the musculoskeletal structure—is highly complex and nonlinear [15, 33–35]; therefore measurement of the stability and flexibility of movement patterns is difficult. One partial solution has been the study of motor development during discrete trial procedures in which a restrained or supported infant is presented with a motor task such as reaching towards an appearing target. However, motor development occurs in more naturalistic environments and contexts, conferring more possibilities for action than those afforded in tightly controlled experimental tasks. Moreover, recent advances in wearable sensors have allowed us to capture the increasing

Table 1: Mean age and number of participants for each age group.

Age Group	Mean Age in Months (SD)	# Participants/Sessions
9 months	9.63 (0.24)	22
12 months	12.72 (1.08)	18
15 months	15.49 (0.25)	20
18 months	18.65 (0.30)	20
21 months	21.64 (0.23)	25
24 months	24.54 (0.49)	26

sophistication of manual behavior in older infants during naturalistic and free-flowing play contexts. Manual play with objects in these contexts is developmentally related to tool use [27, 36, 37], visual object recognition [3, 38, 39], and language [3]. A central contribution of the present study is a new method for estimating spatial-temporal modes of behavior (the shape and size of an attractor region) in the space of all possible hand movements (the state space). We show that, during bouts of manual actions with objects, infants traverse a constrained trajectory in the state space of movement patterns and that the size of their attractor region increases with age: suggesting increased flexibility in manual action patterns.

Our approach was motivated in part by Thelen et al.'s [40] longitudinal study of reaching from onset through the first year of life. Collecting dense recordings of limb movements, Thelen et al. observed the patterns of movement that led up to the emergence of the skill of reaching. Because of the high-dimensional space of the intrinsic dynamics of movements, each successfully produced reach appeared to be unique in its movement patterns. To reduce the dimensionality of kinematic data, Thelen et al. constructed a phase portrait by continuously plotting the relation between movement displacement and velocity. These low-dimensional geometric portraits of patterns of movement revealed stable modes of behavior across reaches and infants. Here, concentrating on the free-flowing actions of reaching for and manually acting with objects during play in older infants, we adapted a novel quantitative protocol for estimating attractor regions [41] across a probabilistic state space akin to a phase portrait.

This quantitative protocol allows us to investigate a number of questions about how manual behaviors change across age and during specific types of actions like reaching and producing manual actions with objects in a free-flowing toy play task. First, little is known about how the motor system changes across age in contexts that are not constrained by discretized trials with specific tasks given by experimenters. Our analysis estimates (1) a probabilistic state space of possible hand movements and (2) an attractor region. The estimated attractor region comprises manual actions that encompass normal modes of spatial-temporal movements that share the same areas in the probabilistic state space. In other words, given all of the possible spatial-temporal movements an infant can make with their hands, movements inside of the attractor region are the most similar movements and movements outside of the attractor region are the least similar movements. The size of the attractor region for any given infant indexes the flexibility of the manual action system, such that a larger region equates to a more flexible system because a larger region comprises more typical hand movements in the state space of all possible hand movements. One of our main hypotheses is that as infants become older, their manual action system becomes more flexible–as indexed by larger attractor regions. We call this hypothesis the *developmental hypothesis*. Our second hypothesis is that manual actions with objects will more often be located in the attractor region of the state space of all possible movements. We call this hypothesis the *attractor hypothesis* because the action of manually acting with an object is an attractor that brings the behavior into the attractor region. Given that our quantitative protocol is novel, testing the attractor hypothesis is important to show that the method is sensitive to changes in manual actions with and without objects.

2. Methods

2.1. Participants. A total of 43 parent-infant dyads participated in the current study. Dyads could participate in a maximum of 6 sessions, from age 9 months to 24 months in three-month increments. This is an age range known for rapid development in sensorimotor behaviors [34]. The current dataset encompasses a total of 131 sessions (see Table 1). A total of 3 participants completed all 6 sessions from 9 until 24 months of age and each participant on average completed 3 sessions (*SD*=1.25). Attrition rates were impacted by a number of factors such as the family moving away from the area or missing a session due to being sick.

2.2. Stimuli. There were three sets of three unique novel toys that were used as stimuli. Each toy was a simple shape of uniform color (red, blue, or green) and similar in size (288 cm^3) and weight (95.25 g). Toys were made from various materials like plastic, hardened clay, aggregated stone, or cloth. Ordering and counterbalancing of stimuli sets occurred for each age group, and, at any one time, one set of three toys was on the tabletop.

2.3. Experimental Room. Infants and parents sat across from each other at a small white table (61 cm x 91 cm x 64 cm). Parents were seated on the ground and infants were seated on a chair that made their eyes, head, and hands approximately the same distance from the table as their parents' (Figure 1). Infants and parents wore head-mounted eye-trackers and motion sensors affixed to both wrists (Figure 1) and the head.

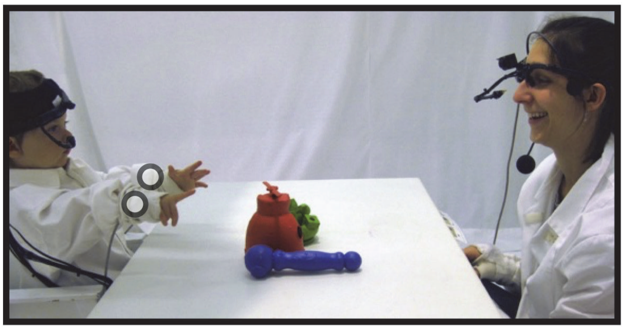

Figure 1: *Experimental setup*. A parent and their infant sit across a table with toys. Motion sensor placements for the left hand and right hand. Circles represent approximate location and are not to scale.

Data collected from the eye-trackers and head-mounted motion sensors were not used in the current study. A Liberty motion tracking system (Polhemus) was used with one sensor embedded in the infant's headband and two sensors embedded in custom-made gloves that were near the infant's left and right wrists. The gloves where fabricated to fit around the wrist and act as a wrist cuff, which did not constrain manual actions nor dexterity. Each sensor generated 6 degrees-of-freedom data:3D positional coordinates (x, y, and z) and 3D rotational orientations (roll, pitch, and yaw) of the head and two hands relative to source transmitters centered above the table. The sampling rate for each sensor was 240 Hz but was downsampled to 60 Hz. All analyses described in the current paper were conducted using 3D positional coordinates. High-resolution cameras (30 Hz) were mounted above the table for a bird's-eye view and also in corners of the room to capture infant and parent perspectives. Video recordings were used in subsequent coding for manual action behavior.

2.4. Procedure. Once the eye-tracking and motion sensors were securely affixed to the infant and parent, an experimenter placed a set of toys on the table and the play session began. Parents were instructed to play naturally with their infant. After approximately 90 seconds of play, an experimenter replaced the toys with a different set and the next trial began. This procedure was repeated and dyads completed up to four trials for a maximum of six minutes of play. Not all dyads completed all of the trials and, therefore, not all total play sessions were six minutes in duration. On average, participants completed 2.77 trials per session (SD = 0.56) for an average session duration of 5.60 minutes (SD = 1.31) per dyad.

2.5. Data Processing and Coding

2.5.1. Manual Action with Object. Using video recordings from the high-resolution camera, the infants' manual actions with objects were manually coded and recorded at a sampling rate of 30 Hz by trained research assistants using a custom coding program. Manual actions with objects were defined as manual behavior that included holding and intentional manual actions like touching and fingering. A second coder coded 9 infants' manual actions from a previous study using the same experimental design with high reliability: Kappa score of 0.96. Proportion of time in manual actions with objects was defined by dividing the total duration of time spent in bouts of manual actions with objects by the total session time. For each session, the preferred hand was identified as the hand with the higher proportion of session time in bouts of manual actions with objects.

2.5.2. Motion Data Processing. For each of the three sensors, Euclidean distance was computed from the three-dimensional position data to reduce the dimensionality to one dimension.

3. Results

3.1. The Development of Manual Actions with Objects Behavior in Infants. The present study examined instances of single-handed manual actions with objects in infants from 9 until 24 months of age. To determine if there were differences across the preferred hand of the infant, we identified the infant's preferred hand by calculating the amount of time using manual actions with objects for each hand. The hand with the greater amount of single-handed manual actions with objects was defined as the preferred hand. The properties of manual actions with objects are described in Table 2. We constructed linear mixed effects (LME) models for each effector (two effectors: preferred hand and nonpreferred hand) and for each age. The duration, proportion, and frequency of manual actions with objects were the dependent measures in the LME models. Infant identity was included as a random effect. Fixed effects for LME models included infant age and bout type. Tukey's Honestly Significant Difference tests were used when multiple comparisons were tested. Duration of bouts of manual actions with objects differed across age ($F[5, 200]$=2.81, p=.02), and specifically bouts of manual actions with objects at 9 months (M=2.03 seconds, SD=3.70) were longer than bouts of manual actions with objects at 24 months (M=1.48 seconds, SD=2.68), p=.03. Duration of manual actions with objects bouts was longer for the preferred hand (M=2.00 seconds, SD=1.80) compared to the nonpreferred hand (M=1.22 seconds, SD=0.93, $F[1, 200]$=2.81, p=.02). Proportion of time in bouts of manual actions with objects was different across age ($F[5, 200]$=2.43, p=.04), but post hoc comparison suggested these differences were nominal. Proportion of time in bouts of manual actions with objects for the preferred hand (M=0.17, SD=0.07) was higher compared to the nonpreferred hand (M=0.06, SD=0.04), $F(5,200)$=233.75, p<.001. Frequency of bouts of manual actions with objects was different across age ($F[5, 200]$=2.81, p=.02), but post hoc comparison suggested these differences were nominal. Frequency of bouts of manual actions with objects for the preferred hand (M=5.92 bouts per minute, SD=2.46) was higher compared to the nonpreferred hand (M=3.73 bouts per minute, SD=2.28), $F(5,200)$=62.91, p<.001. Overall, the preferred hand had longer and more frequent bouts of manual actions with objects compared to the nonpreferred hand.

Table 2: Mean estimates for manual actions with objects properties for the preferred and non-preferred hands (+/-95% CIs in parentheses).

	9 months	12 months	15 months	18 months	21 months	24 months
Manual actions with objects duration (s)						
Preferred	2.03 (1.70, 2.39)	1.50 (1.31, 1.70)	1.96 (1.70, 2.22)	1.71 (1.48, 1.95)	1.68 (1.45, 1.88)	1.48 (1.31, 1.66)
Non-Preferred	1.11 (0.90, 1.34)	1.04 (0.87, 1.23)	1.18 (0.97, 1.42)	1.05 (0.90, 1.22)	1.02 (0.86, 1.17)	0.86 (0.74, 0.99)
Proportion						
Preferred	0.16 (0.12, 0.19)	0.17 (0.13, 0.20)	0.20 (0.17, 0.24)	0.18 (0.16, 0.21)	0.14 (0.11, 0.17)	0.15 (0.13, 0.18)
Non-Preferred	0.05 (0.04, 0.07)	0.08 (0.06, 0.01)	0.07 (0.05, 0.01)	0.06 (0.05, 0.07)	0.06 (0.05, 0.07)	0.05 (0.05, 0.07)
Frequency (per minute)						
Preferred	5.07 (3.73, 6.51)	6.60 (5.32, 7.99)	6.17 (5.35, 7.11)	6.64 (5.55, 7.82)	5.02 (4.26, 5.97)	6.24 (5.52, 6.99)
Non-Preferred	3.02 (2.03, 4.16)	4.69 (3.46, 5.94)	3.48 (2.68, 4.26)	3.49 (2.77, 4.33)	3.51 (2.73, 4.38)	3.89 (3.05, 4.89)

3.2. The Development of Hand Velocity and Displacement. To understand how the dynamics of hand movements developed over time, we first collapsed the x, y, and z coordinates of the preferred and nonpreferred hand's position by calculating their Euclidean distance, also termed displacement (Figures 2(d) and 2(e)). In other words, displacement is a measure of hand position reduced from the x, y, and z coordinates into one value. From the displacement of each hand sensor, we were able to calculate positional velocity (Figures 2(a) and 2(b)). For the preferred (turquoise) and nonpreferred (beige) hand, the average developmental trajectories of positional velocity and displacement are plotted in Figures 2(c) and 2(f), respectively, along with the 95% bootstrapped confidence interval. At a session level, we observed no significant developmental differences in displacement ($F[5, 208]$=0.61, p=.69) or velocity ($F[5, 208]$=2.09, p=.07) of the preferred and nonpreferred hand. To determine whether there was a change in the interaction between displacement and velocity–the actual dynamics of hand movements–we characterized each hand as a phase portrait by creating a 2-dimensional state space comprised of the displacement and velocity values from each hand. In the next section, we will go through each step of the quantitative protocol.

3.3. Estimation of the Attractor Region from Phase Portraits. Prior research has leveraged the dense sampling of cardiac activity, respiration, and body movement to estimate the attractor dynamics of the autonomic nervous system in adult marmoset monkeys while they vocalize [41]. Here we extend the analyses to movement variables from human manual actions in order to capture features of the attractor region for hand movements and any developmental change to these features. We estimated the attractor regions for hand movements by fitting a multivariate Gaussian distribution to the covariance matrix of the hand position data, as follows. The attractor region was estimated on a session-by-session basis for each infant. We first calculated the Euclidian distance between the x, y, and z coordinates for the entire session. Data points that were greater than 2.5 standard deviations away from the mean of the Euclidian distance measure were identified as outliers. We then calculated the velocity of the Euclidian distance and then removed all outlying data points. To control for differences in the location of the infants across sessions and to control for the developmental change in body growth, such as arm length, we z-scored the Euclidian distance and positional velocity measurements. From these normalized Euclidian distance and positional velocity measurements, we can plot the phase portraits for each infant's preferred and nonpreferred hand for every session (Figure 3). We then calculated the covariance matrix of the z-scored positional velocity and Euclidian distance measurements using cov in Matlab. We fit a multivariate normal Gaussian distribution to the data and calculated the contours encompassing the 50th percentile of the distribution. For each Gaussian fit, we calculated the longest distance along the x-axis (velocity), the longest distance along the y-axis (displacement), and the area of the Gaussian. The area of the Gaussian was considered the size of the attractor region. All possible movements in the x-axis and the y-axis represent the probabilistic low-dimensional state space of movements.

3.4. Hypotheses for Attractor Regions of Manual Actions. The method described above allows for specific questions about how the attractor regions of manual actions change over development and during specific types of behaviors. For example, does the size of the attractor region change throughout the first two years of life? Infants use increasingly more complex manual actions throughout development [25, 36, 42–44]. We expect more flexible manual actions to be produced by hand movements with larger ranges of displacement and velocity. Therefore, our developmental hypothesis is that the attractor regions should increase in area across

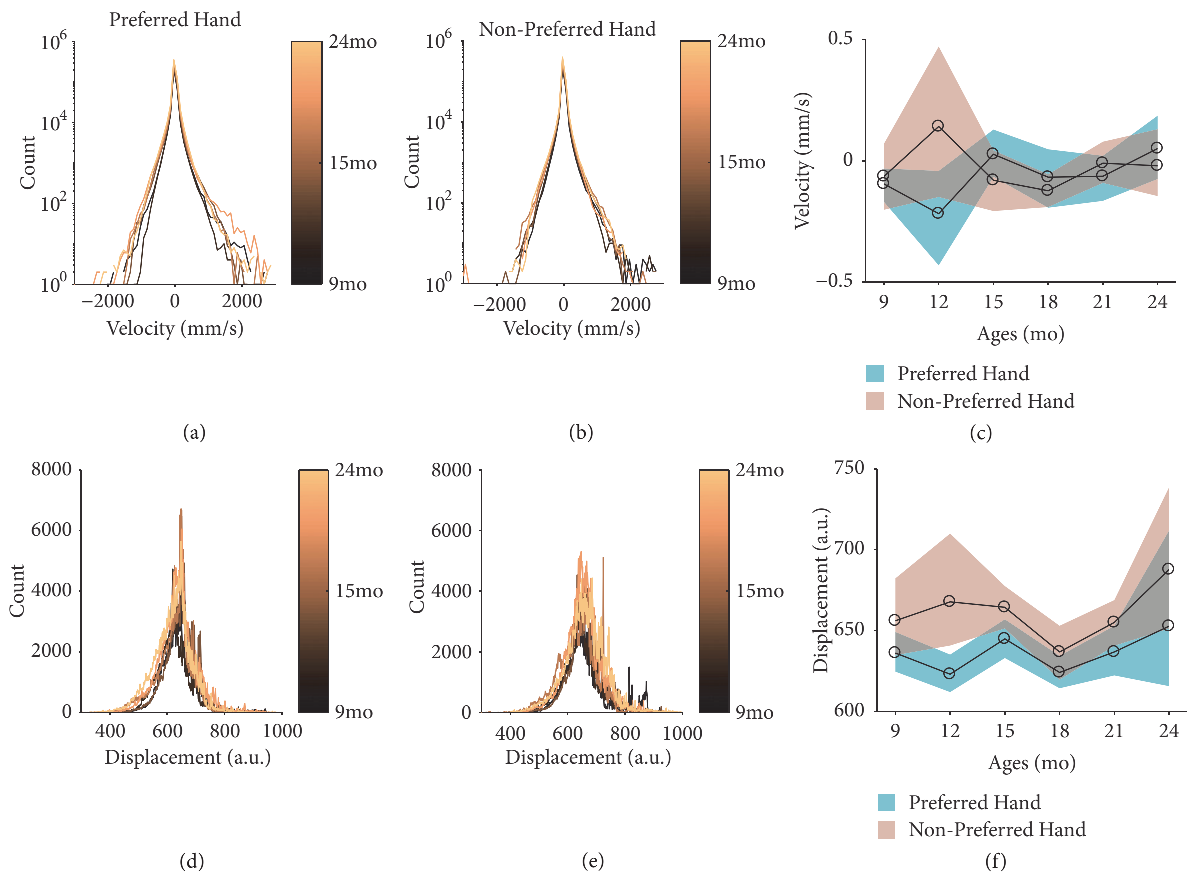

FIGURE 2: *The development of manual actions with objects dynamics.* Histograms for the velocity (a, b, c) and displacement (d, e, f) of the preferred (a, d) and nonpreferred (b, e) hand. Colors indicate age group, with lighter shades indicating older children. The average velocity (c) and displacement (f) for the preferred (turquoise) and nonpreferred (beige) hand. Shaded region indicates the 95% confidence interval.

the developmental period measured, from 9 months until 24 months of age. Increases in the area of the attractor region would suggest a more flexible system of manual actions. A larger attractor region represents a larger range of movement states in the overall state space of movements encompassed by the attractor.

Another feature of our method for estimating attractor regions is that we can investigate the overall amount of time spent inside of the attractor region during specific types of behaviors. For example, what is the proportion of time spent inside of the attractor region during manual actions while manual acting with an object relative to when not manually acting with an object? Our attractor hypothesis is that manually acting with an object is an attractor that moves the manual action system into the attractor region. The behavior of manual actions with objects encompasses many different types of object manipulations. Despite the diversity of object manipulations an infant can perform during manual actions with objects, we expect that the low-dimensional dynamic behavior as observed through the attractor dynamics framework will uncover similar patterns across bouts of manual actions with objects. This is similar to what Thelen et al. [40] observed in reaching: high-dimensional movements were highly variable during reaching, but when observed in low-dimensional phase portraits, the behaviors were actually quite similar showing evidence for a stable limit cycle. Specifically, the attractor hypothesis would suggest that (1) the manual action system spends more time inside of the attractor state during bouts of manual actions with objects and (2) the manual actions with objects are what moves the manual action system into the attractor region.

3.5. The Development of Attractor Regions. The phase portraits in Figures 3(d) and 3(h) demonstrate the breadth of data along two axes: displacement and velocity. The fitted Gaussian attractor regions were unrestrained and had no prior conditions for fitting, besides being centered to the mean of the entire session's data and bounded by the covariance matrix and 50th percentile of the session. Thus, attractors could be tilted and were not necessarily aligned to the vertical and horizontal axes. The nontilted attractor regions are plotted in Figure 4(a) (preferred hand) and Figure 4(e) (nonpreferred hand). To determine whether the estimated attractor regions captured meaningful developmental change, we sought to measure three features of the attractors over developmental time: the range of (1) velocity and (2) displacement and (3) the area of the attractor. We measured the greatest range of velocity and displacement for each attractor by calculating

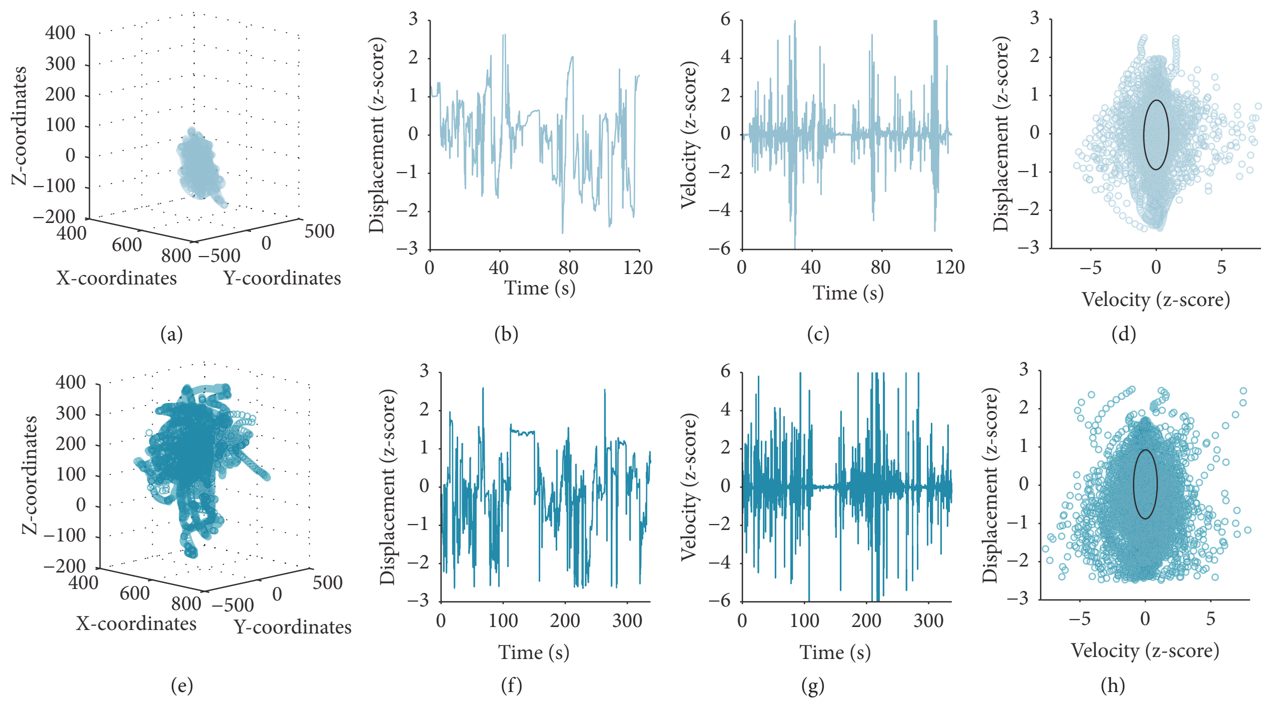

FIGURE 3: *Exemplar of preferred hand movement for the same child at 9 months (a–d) and 24 months (e–h) of age.* (a, e) Session data for preferred hand position. (b, f) Euclidian distance for the preferred hand position data. (c, g) Positional velocity derived from the Euclidian distance of preferred hand position. (d, h) Phase portraits of preferred hand velocity (x-axis) against displacement (y-axis). The black ellipse represents the calculated Gaussian fit attractor for the phase portrait.

the longest vertical (displacement, Figures 4(b) and 3(f)) and horizontal (velocity, Figures 4(c) and 4(g)) line that could be drawn within the bounds of the attractor. The area of each Gaussian attractor region was plotted across development for preferred (Figure 4(d)) and nonpreferred (Figure 4(h)) effectors.

We constructed LME models for each effector (two effectors: preferred hand and nonpreferred hand) and for each phase portrait property (three properties: displacement axis, velocity axis, and area), accounting for nine total LME models. Fixed effects for these models included infant age in months. Tukey's Honestly Significant Difference tests were used when multiple comparisons were tested.

For the preferred hand, there were no age differences for the displacement axis, $F(5,83)=0.70$, $p=.62$. There were age differences for the velocity axis ($F[5,83]=4.87$, $p<.001$) and for area ($F[5,83]=4.16$, $p=.002$), suggesting that there were increases in both properties across age. For the velocity axis, the range of the velocity axis was significantly smaller at 9 months ($M=1.68$, $SD=0.23$), compared to 18 months ($M=1.82$, $SD=0.13$, $z=3.18$, $p=.02$), 21 months, ($M=1.80$, $SD=0.13$, $z=2.98$, $p=.03$), and 24 months ($M=1.83$, $SD=0.11$, $z=3.42$, $p=.008$). Attractor region area was significantly smaller at 9 months ($M=2.51$, $SD=0.36$), compared to 18 months ($M=2.73$, $SD=0.19$, $z=2.93$, $p=.04$) and 24 months ($M=2.74$, $SD=0.16$, $z=3.65$, $p=.004$). Total area at 12 months ($M=2.52$, $SD=0.24$) was significantly smaller than total area at 24 months, $z=3.19$, $p=.02$. For the nonpreferred hand, there were no age differences for the displacement axis ($F[5,83]=1.54$, $p=.19$), the velocity axis ($F[5,83]=0.91$, $p=.48$), or area, $F(5,83)=0.88$, $p=.50$.

Overall, these results suggest that the manual action system becomes more flexible across the first few years of life, and this depends on hand preference. As indicated by an increase in the size of the attractor region throughout infancy for the preferred hand, the manual action system of the preferred hand becomes more flexible. However, we did not observe such a trend for the nonpreferred hand.

3.6. Manual Action with Objects: An Object Is an Attractor. To determine the amount of time spent in typical or less typical modes of behavior during manual actions, we computed the relative proportion of time inside or outside of the attractor region for the preferred and nonpreferred hands during bouts when (1) the hand was manually acting with an object, (2) the other hand was doing manual actions with an object (e.g., relative proportion of time the preferred hand is inside and outside of the attractor ellipse when the nonpreferred hand is manually acting with an object), and (3) neither hand is manually acting with an object (Figures 5(a) and 5(b)). If manual actions constrain body movements, we expect higher proportions of each hand inside the attractor region during bouts of manual actions with an object (of either the same or the other hand), relative to bouts when neither hand is manually acting with an object (Figures 5(c) and 5(d)). See Table 1 for bout properties of manual actions with objects for the preferred and nonpreferred hands.

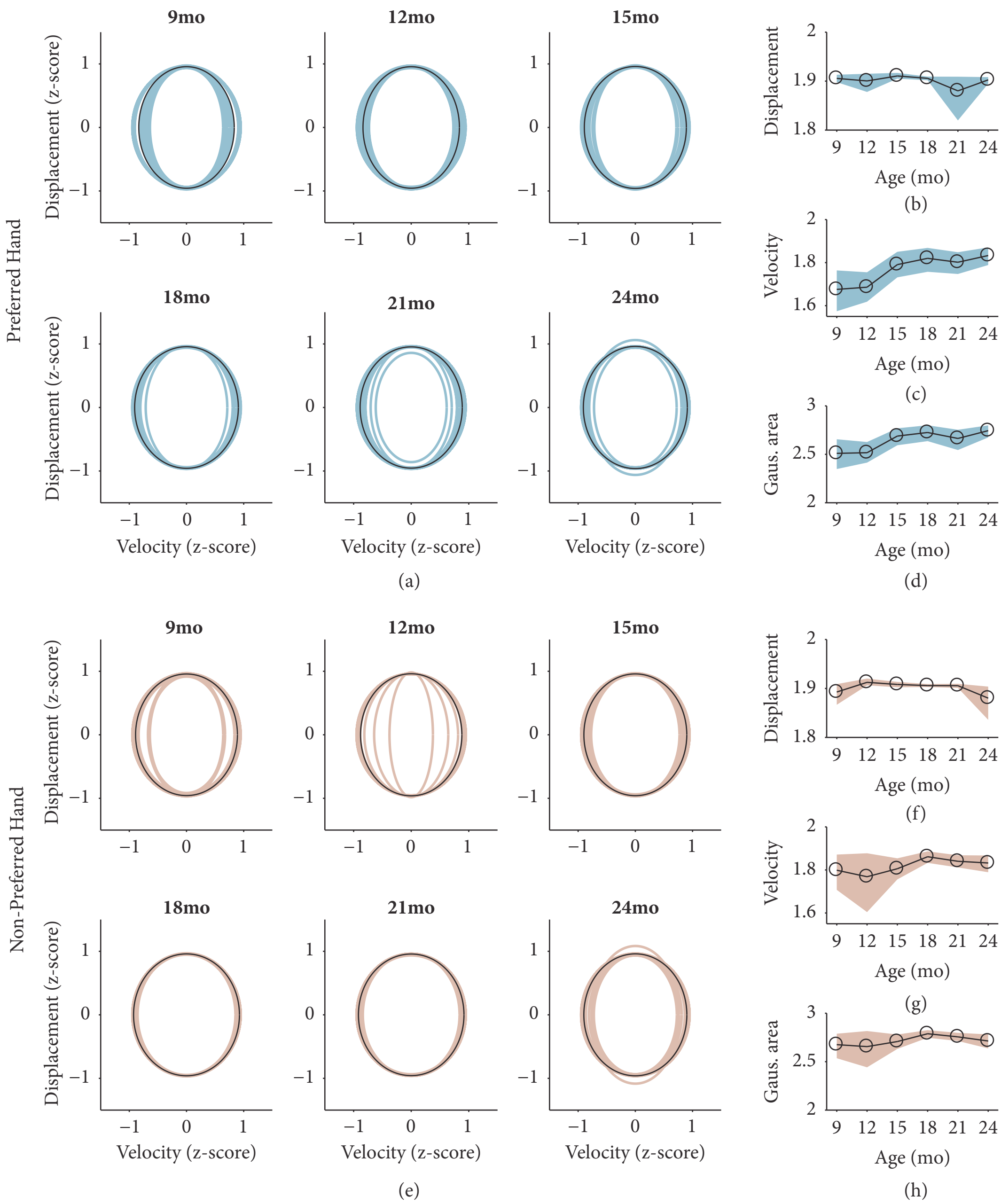

FIGURE 4: *Analyses of the calculated Gaussian fit attractor regions across development*. (a, e) The resulting attractor regions for the preferred hand (a, turquoise) and nonpreferred hand (e, beige) based on the phase portrait for each participant in the study. The average attractor region is plotted in black. The x-axis represents z-scored velocity while the y-axis represents z-scored displacement. (b, f) The development of the longest line parallel to the y-axis bounded by the attractor region for the preferred hand (b) and nonpreferred hand (f). (c, g) The development of the longest line parallel to the x-axis bounded by the attractor region for the preferred hand (c) and nonpreferred hand (g). (d, h) The development of the area of the attractor region for the preferred (d) and nonpreferred (h) hand. (b–d, f–h) Black circles indicate the average for each age group while the shaded region indicates the bootstrapped 95% confidence intervals.

We constructed LME models for each effector (two effectors: preferred hand and nonpreferred hand) and for each type of bout (the same hand manually acting with an object, other hand manually acting with an object, and no manual actions with an object). Because we are interested in the relative proportion of time inside and outside of the attractor region, we computed a delta index, subtracting the total amount of time outside of the region from the total amount of time inside of the region. A positive delta index indicates more time inside of the region relative to outside of the region. The delta index was the dependent measure in the LME models. Fixed effects for LME models included infant age and bout type. In preliminary models, we included infant age as a fixed effect but observed no

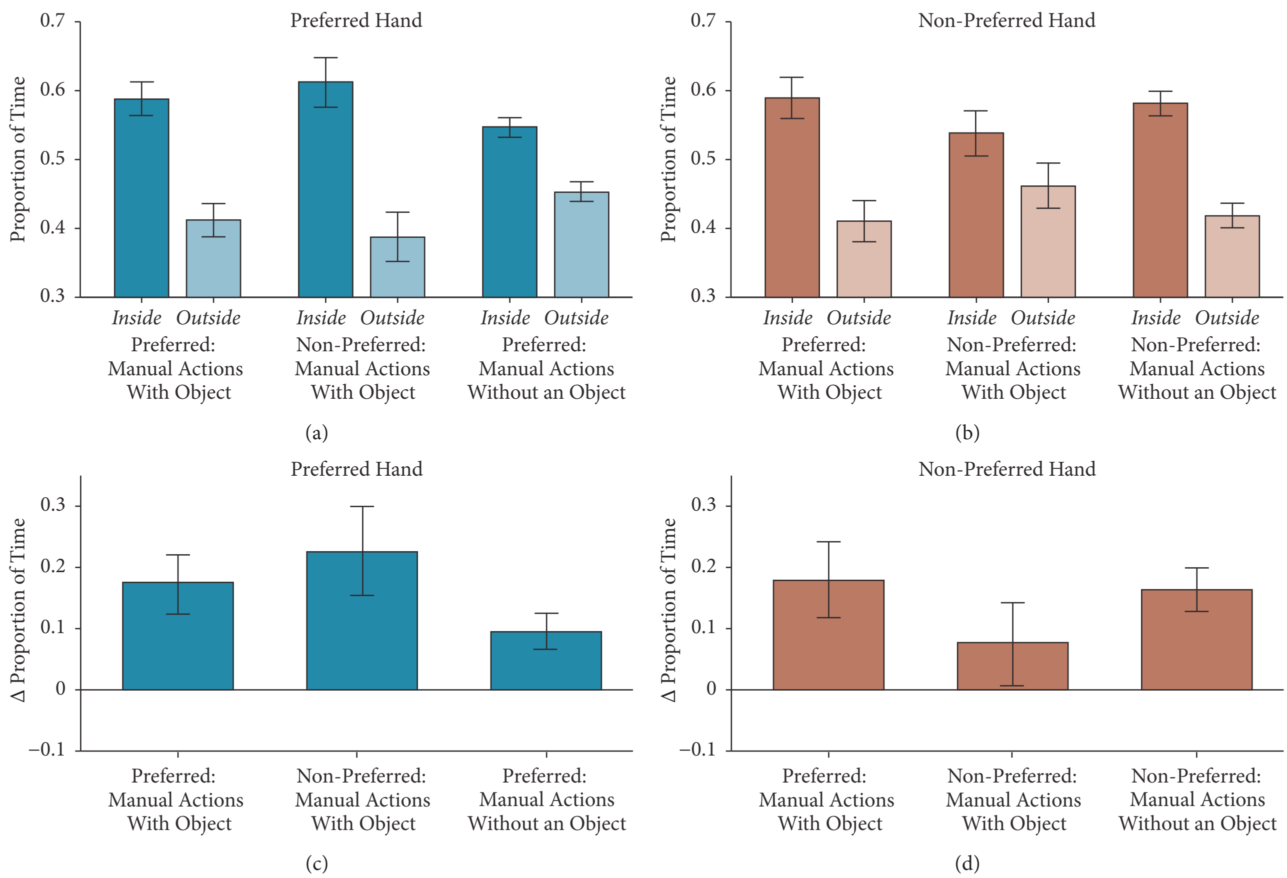

FIGURE 5: *Manual actions with objects inside and outside of the attractor region*. (a, b) The proportion of time inside and outside of the attractor region for the preferred (a, turquoise) and nonpreferred (b, beige) hands for three types of events: manually acting with an object with the preferred hand, manually acting with an object with the nonpreferred hand, and no manual action with an object. Lighter shades indicate proportion of time spent outside of the attractor. Error bars indicate the bootstrapped 95% confidence interval. (c, d) The difference in proportion of time inside and outside of the attractor for each event type for preferred (c, orange) and nonpreferred (d, green) hands. Error bars indicate the bootstrapped 95% confidence interval.

significant differences, and we therefore omitted infant age in all reported analyses.

For the preferred hand, we constructed two LME models. In the first model, the delta index of the preferred hand was the dependent measure and bout type (preferred hand manually acting with an object, nonpreferred hand manually acting with an object, and no manual action with an object) was the fixed effect. We observed a significant main effect of bout type, $F(1{,}260)=6.48$, $p=.002$. We observed that the delta index for the preferred hand when the preferred hand was manually acting with an object ($M=.18$, $SD=.28$) was marginally higher compared to bouts of not manually acting with an object ($M=.09$, $SD=.17$), $z=-2.26$, $p=.06$. We also observed that the delta index for the preferred hand when the nonpreferred hand was acting upon an object ($M=.22$, $SD=.40$) was significantly higher compared to bouts of not manually acting with an object, $z=3.56$, $p=.001$.

We constructed a second model to test for overall differences in delta indices for the preferred hand, when either hand was manually acting with an object compared to bouts of not manually acting with an object. In the second model, the delta index was the dependent measure and bout type (either hand manually acting with an object, no manual action with an object) was the fixed effect. We observed a significant main effect of bout type ($F[1, 261]=11.24$, $p<.001$), suggesting that the delta indices for the preferred hand during bouts of either hand manually acting with an object ($M=.20$, $SD=.35$) were higher compared to bouts of not manually acting with an object ($M=.09$, $SD=.17$).

For the nonpreferred hand, we constructed two LME models. In the first model, the delta index of the nonpreferred hand was the dependent measure and bout type (preferred hand manually acting with an object, nonpreferred hand manually acting with an object, and no manual action with an object) was the fixed effect. We observed a significant main effect of bout type, $F(1{,}260)=3.67$, $p=.03$. We observed that the delta index for the nonpreferred hand when the preferred hand was manually acting with an object ($M=.18$, $SD=.35$) was higher compared to when the nonpreferred hand was manually acting with an object ($M=.8$, $SD=.39$), $z=-2.51$, $p=.03$. We also observed that the delta index for the nonpreferred hand when the nonpreferred hand was manually acting with an object was marginally lower compared to bouts of not manually acting with an object, z=-2.13, p=.08.

Similar to what was done for the preferred hand, we constructed a second model to test for overall differences in delta indices for the nonpreferred hand, when either hand was manually acting with an object compared to bouts of not manually acting with an object. The main effect of bout type was not significant ($F[1, 260]$=1.01, p=.32), suggesting that the delta indices for the nonpreferred hand during bouts of either hand manually acting with an object (M=.13, SD=.37) were not different from indices during bouts of not manually acting with an object (M=.16, SD=.20).

These results suggest that when the preferred hand is manually acting with an object, the manual action system–across both hands–is more constrained in the spatial and temporal dimensions. Moreover, when the nonpreferred hand is manually acting with an object, the nonpreferred hand is more likely to be in less probable locations in the state space of possible hand movements. Overall, these results suggest that the preferred and nonpreferred hands have different modes of spatial-temporal behaviors during bouts of manual actions with objects.

3.7. The Attractor Dynamics of Manual Actions with an Object. We next sought to determine how the average movement trajectory of hand position during manually acting with an object related to our estimated attractor regions. We took the position of the preferred and nonpreferred hand 3 seconds before and 5 seconds after the onset of a manual action with an object. This resulted in a total of 11,360 instances of manual actions with objects across all subjects and age groups with an average of 1,893 instances of manual actions with objects per age group (SD = 552). For each instance of manual actions with objects we calculated the Euclidean distance of the x, y, and z coordinates as well as the velocity of the Euclidian distance. We then averaged the Euclidean distance and velocity for each age group and z-scored the resulting average. For each age group, we plotted the z-scored average displacement and velocity measures against the average attractor region for the preferred (Figure 6(a)) and nonpreferred (Figure 6(b)) hands.

Across all ages, the dynamics of manual actions with objects appear remarkably similar. Beginning three seconds before the onset of manual action (Figure 6, black line), there are consistent excursions around the state space before a gradual return into the attractor region once a bout of manual actions with objects begins (Figure 6, red line). For the duration of the bout of manual actions with objects, the trajectory largely stays within the attractor region, even until after the manual action has ended (Figure 6, gray line). This dynamic is consistent across both preferred and nonpreferred hands and across age groups, suggesting the low-dimensional trajectories through the state space before, during, and after manual actions with objects do not differ much during development.

4. Discussion

The current study introduced a novel analytical paradigm for estimating attractor regions of manual actions. The paradigm was applied to a large longitudinal corpus of hand movements during infant-caregiver toy play. We observed that the size of attractor regions increased throughout development, suggesting that the manual action system becomes more flexible throughout development. We also observed that, in a state space of possible movements, hand movements from the preferred hand during bouts of manual actions with objects were more likely to be in the attractor region.

The proposed *developmental hypothesis* suggests that attractor regions should increase in area throughout the first two years of life. We observed partial evidence for this hypothesis. Across development, we demonstrated that the attractor region for the preferred hand increases in both area and range of velocity (Figures 4(c) and 4(d)). The nonpreferred hand, in contrast, showed no developmental change along velocity, displacement, or area (Figures 4(f)–4(h)). The observed increases in the area of the attractor region for the preferred hand suggest a more flexible system supporting its actions. A larger attractor region covers a larger area of displacement and velocity, facilitating a more diverse range of movements. Throughout the first few years of life, infants perform increasingly complex toy play behaviors [25, 36, 42–44]. Our results suggest that these complex behaviors are supported by a manual action system that is becoming more flexible. It is important to note the distinction between a flexible system and a more controlled system. Our results point specifically to the *flexibility* of a system, whereas other methods have been successfully implemented to measure control, which, in the same topology as our phase portraits, would be in the form of observing stable limit cycles [40, 45].

The proposed *attractor hypothesis* suggests that manual action with an object is an attractor and therefore we should (1) observe the manual action system to spend more time inside the attractor region and (2) observe that the manual action with an object is what moves the manual action system into the attractor region. We observed that when either hand was manually acting with an object, the preferred hand movements were more likely to be inside the attractor region than outside of the attractor region. This observation provides partial support for the attractor hypothesis. We also observed that the nonpreferred hand movements were more likely to be inside of the attractor region when the preferred hand was manually acting with an object compared to when the nonpreferred hand was manually acting with an object. Previous research has shown that as the motor system develops, the so-called motor overflow – one limb showing similar behavior as the other limb during specific actions – decreases, which has been suggested to mark the emergence of more specialized motor actions such as unimodal manual actions [46, 47]. Our results do not shed any new light on the evidence for motor overflow but rather point to the increased complex behavior such as unimodal manual actions and role-differentiated bimodal action that become more prevalent going into the second year of life [23] (Goldfield and Michel, 1986; Kimmerle, Mick, and Michel, 1995; Kotwica, Ferre, and Michel, 2008), which are the suggested consequences of the cascading effects of motor overflow. Our current analyses were agnostic as to the exact trajectories of manual actions with objects and did not directly compare the

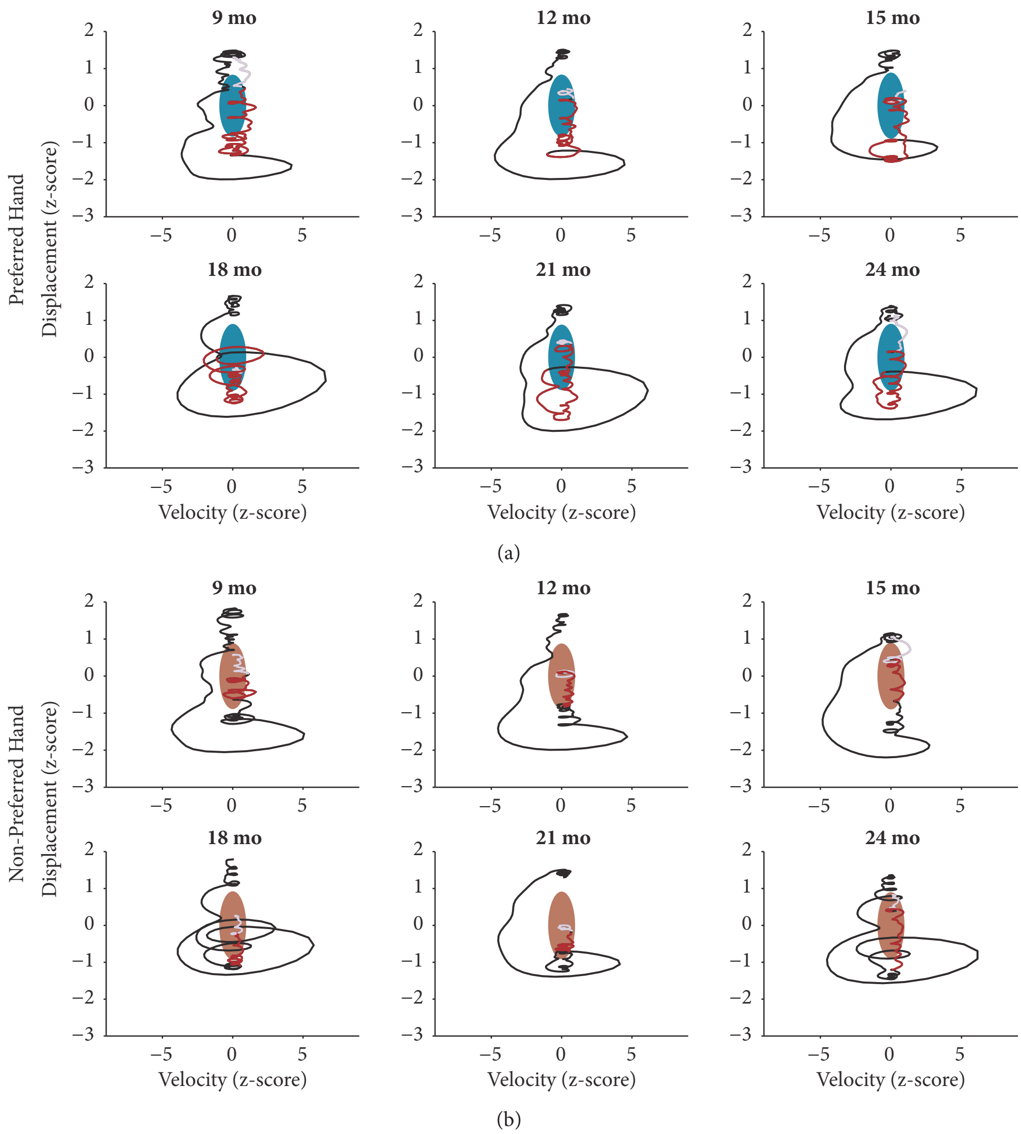

Figure 6: *The attractor dynamics of manual action with objects.* (a, b) The average attractor region for each age group for the preferred (a, turquoise) and nonpreferred (b, beige) hand. Line indicates the average z-scored velocity and z-scored displacement for 3 seconds before the onset of manual action and 5 seconds after manual action's onset. The black line indicates the time period 3 seconds before the onset of manual action. The red line indicates the manual action behavior with its duration equal to the average duration of manual action for that age group. The gray line indicates the action's offset.

trajectories of each hand. Instead, the increased proportion of time the preferred hand remained in the attractor region during nonpreferred manual actions with objects suggests that the nonpreferred hand's manual actions with objects still recruit effort from the preferred hand, perhaps implicating a mechanism similar to motor overflow. Further investigation would be necessary to link the observed phenomena with the concept of motor overflow, especially at younger ages when motor overflow has been known to occur.

Finally, when we plot the average trajectory of hand movements during manual actions with objects through the probabilistic state space of movements, we find that manual actions with objects have consistent trajectories that end inside of the attractor region across all age groups. Beginning three seconds before the onset of manual actions with objects, there is an excursion away from the attractor region. The onset of manual actions with objects occurs just before the movement in the state space approaches the attractor region for the preferred hand. For the nonpreferred hand, movements are already in the attractor region at the onset of a manual action. For both preferred and nonpreferred hands, manual actions with objects are characterized by a period of low velocity and little movement along the displacement axis. While this study only looked at instances of single-handed manual actions with objects, it is likely that two-handed manual actions with objects would share similar dynamics.

The functional result of low hand velocity and movement during manual action is the stabilization of the object.

Putatively, this would maximize visual information that could be processed from the object while it is in view. While this study did not measure the amount of looking time of the held object, prior research suggests that attention to objects requires sensorimotor coordination that stabilizes body movements and likely facilitates learning [48, 49]. In our framework, it is intriguing to consider attractors from other modalities. For example, does gaze behavior–which occurs at a faster timescale relative to manual actions–push manual actions inside and outside of attractor regions? Alternatively, it is possible that the slower-changing dynamics of manual actions constrain the faster-changing dynamics of gaze behaviors [50]: manual actions with objects are attractors pushing gaze behavior into modes of sustained attention.

This study contributes to a number of areas in the literature. Many previous studies have studied how the motor system reorganizes when learning new skills and how the motor system changes throughout development [8, 11, 21, 22, 25, 26, 28, 36, 42, 43]. However, our study is the first–to our knowledge – to index the development of flexibility of manual action in a natural free-flowing context throughout the first two years of life. By showing that the preferred hand becomes more flexible across development–as observed by increased attractor region size – we add more insight into the developmental trajectory of the manual action system. It should be noted that a limitation of the current paper is that the level of analysis of manual actions with objects is only informative to whether or not manual actions include or do not include an object. Future work needs to determine whether specific types of manual actions with objects, such as holding, touching, and fingering, generate different types of phase portraits across development. Our study also contributes a new method for reducing the dimensionality of behavior down to a phase portrait and then quantifying properties such as the size of an attractor region or the time inside or outside of an attractor region. At the outset of this paper, we discussed Thelen et al.'s [40] conceptual treatment of a phase portrait of reaching behaviors as a motivation for our new method. Although previous research has used phase portraits of specific behavior as a topological space for understanding stable motor behavior [15, 40, 45, 51–55], most of this work focused on periodic behavior (e.g., reiterant speech) and not on quantifying properties of phase portraits constructed from aperiodic behavior like natural free-flowing dyadic toy play. Therefore, the current study provides a novel method for indexing properties of phase portraits assembled from natural behaviors that would not be classified as periodic.

The present study leverages a dense corpus of hand movements during parent-infant play and demonstrates one tractable way to quantitatively define the attractor region for hand movements. We demonstrate developmental changes in the attractor dynamics of the preferred hand, consistent with the emergence of flexible motor behavior. We also demonstrate that the manual action with objects itself occurs within the attractor region of the limb's movement, a region characterized by low velocity and low speed. This study serves as a first step in quantitatively defining the development and function of attractor dynamics in manual action.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Authors' Contributions

Jeremy I. Borjon and Drew H. Abney contributed equally to this work.

Acknowledgments

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Research Article

Categorical Cross-Recurrence Quantification Analysis Applied to Communicative Interaction during Ainsworth's Strange Situation

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The goal of this study was to characterize the degree of structuring of verbal and motor behaviours, unfolded during the application of an procedure called the Strange Situation. This procedure is used for assessing children's attachment quality during early stages of their development. Many studies have demonstrated that communicative interactions share features with complex dynamic systems. In such studies, estimations of degree of structure have been used to characterize the system's synchronization. Thus, assuming that processes of communicative interaction occur in the Strange Situation procedure, it was expected to find traces of synchronization. The metrics were estimated through a Categorical Cross-Recurrence Quantification Analysis applied to the behaviours of individuals and dyads. Two applications of the Strange Situation were implemented and recorded. Verbal and motor interactions among children, caregivers, and strangers were transcribed, categorized, and organized as time series. From each time series of original behaviours, randomized time series were created. Measures of recurrence extracted from Recurrent Plots, such as determinism, entropy, maximum line, laminarity, and trapping time, were calculated. Original and randomized time series were compared in terms of these measures. Results indicated that communicative interaction during the Strange Situation had a structure that mimics properties observed in social interactions where synchronization emerges. In our case, verbal behaviours were more prone to synchronization than motor behaviours, in both individuals and dyads, even though this pattern was more salient among caregivers and strangers than children. The relevance of having measures that can capture synchronization during the administration of the Strange Situation is discussed. Our preliminary findings allow us to point out that the application of RQA and C-RQA to the Strange Situation could not only contribute to methodology, but also contribute to emphasizing the role of coupling in communicative interaction generated by the application of this procedure to measure attachment patterns.

1. Introduction

Human communicative interaction is a phenomenon that behaves as a complex dynamic system [1–3]. The reason for the complexity observed in communicative interaction is because the number of components and relations between them increases to such an extent that a new phenomenon emerges, and this phenomenon cannot be explained by the constitutive components [2]. Complex dynamic systems, whether physical, chemical, biological, or social, share distinctive properties, among which synchronization is relevant. In broad terms, synchronization refers to the activity of two or more components at the same time or rate. In other words, this process occurs when two or more systems recurrently share a trajectory over a certain period [4].

Synchronization has shed light on the understanding of the development, permanence, and fluctuation of a complex system. Research conducted under the dynamic system approach proposes that human communicative behaviour—at the intra- and interindividual levels—produces synchronization and coupling [2]. Concordantly, findings indicate that some social-communicative interactions have characteristics of a complex dynamic system, where synchronization is a pivotal attribute [5].

Evidence of synchronization of intraindividual behaviours has been found in a series of perceptual [6–8], motor [9–12], and simple decision tasks [13–16]. Signs of synchronization between individuals have been observed in cooperative and noncooperative situations; and traces of coupling have been observed in linguistic and nonlinguistic interactions. Taking these results into account, it has been proposed that synchronization can be modulated by contextual factors [17]. For example, in a social context with negative valence, lower levels of synchrony were detected among the participants. Vink et al. [18] systematized scientific research and reported greater levels of synchronization between dyads when self-reports of rapport were described in terms of more intensity. Hove and Risen [19] found levels of sympathy were positively associated with levels of synchronization between participants. They also observed that when a partner (confederate) came later to the experiment to perform a task there were low levels of interpersonal synchrony between participant and confederate.

Complementarily, other studies have identified that coupling dynamics also vary depending on the conversational context. When a person speaks to a listener who is located somewhere else, better levels of understanding were observed with a delay of two seconds [20]. With this delay, it was also found that gazes exhibit synchronization and coupling. On the other hand, when two persons speak face to face, in real time, alternating the role of speaker and listener, the optimal coupling time is reduced to zero seconds [21].

As a result of communicative interaction, synchronization plays an important role for social development [22]. It has been suggested that synchrony in mother-child interactions is not only significant for language acquisition but also significant for the development of social relationships and intersubjectivity. Along the same line, Stern [23] found that a lack of synchronization between parents and their children could affect the latter's behaviour and affective states.

A longitudinal study developed by Siller and Sigman [24], with parents of children with autism, found that the communication between caregivers and children was predicted by the degree of synchronization in the interaction. Tunçgenç and Fawcett [25] conducted two studies in which children who were 9 months old and 12 months old were located in social and nonsocial contexts. They found that 9-month-old babies showed preference for objects in synchronous movement, regardless of whether the object was in a social context or not. However, 12-month-old infants showed a preference only for stimuli in a social context that moved synchronously with respect to them. Thus, synchronization of the movements was an important factor to guide the social preferences of babies [25].

In sum, human communicative behaviour is considered a complex dynamic system, where synchronization is a relevant attribute. Signs of synchronization have been detected in various types of behaviour and cognitive processes, in both individuals and groups. There is evidence that levels of synchronization can affect and be affected by the initial conditions of the environment or by the affective-emotional state of the individuals. Furthermore, based on the aforementioned empirical background, it is possible to conjecture that the presence of synchronization in behaviour is an early marker of healthy development and that synchronization enables predicting the adaptive behaviour of humans in the early stages of their development.

The Theory of Attachment was proposed Bowlby [26] to understand how these early communicative behaviours and the degree of social adaptive behaviour are configured by the caregiver-child interaction. This theory explains how the first relationships of children with their caregiver are formed, based on the concept of attachment, which is described as "(. . .) the process by means of which children establish and maintain a special relationship with another individual who is considered better able to face the world" [27, p. 40]. Patterns of attachment are the result of instinctive responses for the protection and survival of the child. This process is considered as the bridge of early development and later development of social relations. Thus, the bond of attachment could be considered as the relationship established between babies and their caregivers, which influences their development and subsequent well-being.

There is an increasing amount of research about attachment in the early stages of development, personality development [28, 29], social adjustment [23, 24], as well as the development of psychopathology [30]. The collected background information indicates that the configuration of a particular attachment pattern is the result of an interaction between the natural dispositions of the child and the communicative and bonding patterns that caregivers manifest in a critical period [21]. Disruptions in the period in which this early bond is configured can have negative effects, of great impact, on the lives of individuals.

Patterns of attachment are observed under an experimental procedure called the Strange Situation (SS) [31]. The SS, developed by Ainsworth and colleagues, is the gold standard method to assess the quality of infant-caregiver attachment bond [32]. By proposing a mildly to moderately stressful experience for the infant, this laboratory assessment procedure activates the infant's attachment behaviour addressed to the attachment figure (the caregiver). The increase of the infant's stress activates the infant's attachment behavioural system. These attachment behaviours reveal how the infant organizes his/her expectations regarding the availability of the adult and how he/she can use the caregiver in order to return to calm. Once the infant is reassured, the attachment behavioural system is deactivated, and the exploration behavioural system is activated, evidencing the balance between attachment and exploration [33]. Thus, this procedure aims to identify patterns of attachment between the child and his or her primary caregiver in a laboratory situation where the child's stress is gradually increased by the presence of a stranger and two brief separations from the caregiver. The procedure is composed of eight episodes with a duration of three minutes each [30]. Episodes 5 and 8 are the moments in which the caregiver meets with the child, after having been separated in the previous episodes. The child's reactions are scored and categorized according to four criteria: Proximity and contact seeking; contact maintaining; avoidance of proximity and contact; and resistance to contact and comforting. Finally, according to Ainsworth

[31] and Ainsworth et al. [32], children's reactions under the Strange Situation are classified into four patterns of attachment: (B) Secure: This pattern describes a child who uses the caregiver as a safe base for exploration and can manifest stress behaviour during separation. During the meeting, the child actively seeks caregiver contact through behaviours such as smiles, vocalizations, gestures or physical approach. (A) Insecure Avoidant: This pattern describes a child that shows exploration behaviours but displays few affective behaviours or rarely uses the caregiver as a safe base. During the separation, the child shows slight or no sign of stress. At the meeting, the child tends to avoid contact with the caregiver, such as avoiding gaze and physical contact or focusing attention on toys rather than the caregiver. (C) Resistant Insecure: This pattern depicts a child that during the separation seems extremely stressed. At the meeting, the child usually alternates contact and seeking of the caregiver with signs of rejection, even tantrums towards the caregiver. The child can also be very passive or show behaviours that denote anger. (D) Disorganized Insecure: In this pattern, the child expresses a series of contradictory or incomplete behaviours that would denote a lack of structure, such as interrupted movements, stereotyped movements, freezing/stilling, indicators of fear/apprehension, disorientation, and confusion towards the caregiver [21].

From a dynamic complex system perspective, these attachment patterns should interact with other variables to give rise to a particular type of interaction [2, 8]. Furthermore, these patterns of attachment would also be an integral part of the synchronization with other people. Generally, children's attachment would be an important ingredient for synchronization of behaviours observed in social interactions with adults [11, 14, 34]. Thus, as the SS is an experimental protocol that promotes social-communicative interactions, and social interactions have shown attributes of complex dynamic systems, it was hypothesized that traces of synchronization between dyadic interactions of caregivers, strangers and children could be found.

Research in human communicative interactions has shown that synchronization is nonstationary; it experiences fluctuations and transitions [35, 36]. From a traditional perspective, these aspects are usually controlled or avoided because they add error to the results. However, from a dynamic system approach these aspects, rather than avoided, must be incorporated due to their informative nature. Abrupt changes in postures, introduction and changes of topics, and breaks in the continuum of the conversation, among other factors, could be indicative of qualitative shifts in the mental states of individuals in response to a particular situation [35, 37]. These behaviours are not isolated but rather chained, and they express a pattern that can be identified when are repeated over time. We hypothesized that Ainsworth's Strange Situation, even though it is a highly standardized protocol, has communicative aspects that show traces of relative synchronization between the actors. These signs of synchronization should be identified whether the behaviour is analysed over time, incorporating all aspects of the dynamics, such as fluctuations, transitions and stationarity.

Researchers in the field of dynamic systems have developed a series of techniques and parameters to study synchronization without abandoning its critical aspects, such as nonstationarity, fluctuations, and transitions. One technique that has proven to be useful in the analysis of system synchronization is the Recurrence Quantification Analysis (RQA) [38]. RQA is a multidimensional nonlinear method used to discover attractors from tenuous correlations and subtle repetitive patterns in a time series where the data are noisy, irregular, and with many factors or dimensions affecting their configuration [8, 39, 40]. RQA does not require additional treatment or assumptions about data distribution or size, and it can be applied to both linear and nonlinear variables [8, 39, 41]. Measures extracted by mean of RQA are estimated from recurrence plots (RPs). As depicted in Figure 1, the RP is a graphical representation of a matrix of recurrence that highlights aspects that cannot be detected in the original data set. In formal terms, the RP is an autocorrelation of $x_{(t)}$ with $x_{(i)}$ through the abscissa and $x_{(j)}$ through the ordinate. Only points that satisfy the condition $x_{(i)} = x_{(j)}$ are plotted [12, 41, 42]. From a RP, several quantitative and reliable measures can be estimated, such as the percentage of recurrence that quantifies the proportion of recurrent points that fall within the recurrent plot with a specified radius. The percentage of determinism quantifies the degree of randomness based on the proportion of recurrent points that form a diagonal line, called identity line [43]. Determinism allows knowing if future states of the system are determined by their previous states. Periodic signals can produce long diagonal lines; chaotic signals can generate short diagonal lines, and, finally, stochastic signals cannot generate any diagonal line at all. Entropy represents the uncertainty based on Shannon's entropy, which identifies the degree of disorder expressed by a system. This measure is calculated from the lengths of all diagonal lines that are organized in a histogram according to their distribution. For simple periodic systems, in which all diagonal lines have equal length, the expected entropy is equal to zero. The maximum line represents the length of the longest diagonal line on the RP when the diagonal line of identity has been excluded. Hence, it is a measure of system stability. If the length is shorter, the signal is chaotic, and if the length is larger, the signal is more stable [8].

Cross-Recurrence Quantification Analysis (C-RQA) is used with signals coming from two interacting systems [44–50]. C-RQA, like RQA, quantifies coordinative patterns based on an analysis of the sequence of behaviours performed in real time [40, 41]. Figure 1 shows RPs with interesting features, which can be quantified in various ways [38]. One way is to focus on the diagonal line structures, because they depict a sequence of iterations. When the focus is on vertical lines, two additional measures can be estimated that are considered more informative in terms of the structure of two interacting signals: Percentage of laminarity that represents the proportion of recurrence points that form vertical lines. The laminarity percentage is similar to that of determinism, except that it depicts the proportion of recurrent points comprising vertical line structures rather than diagonal. Finally, there is another measure called trapping time, which represents the mean length of vertical lines.

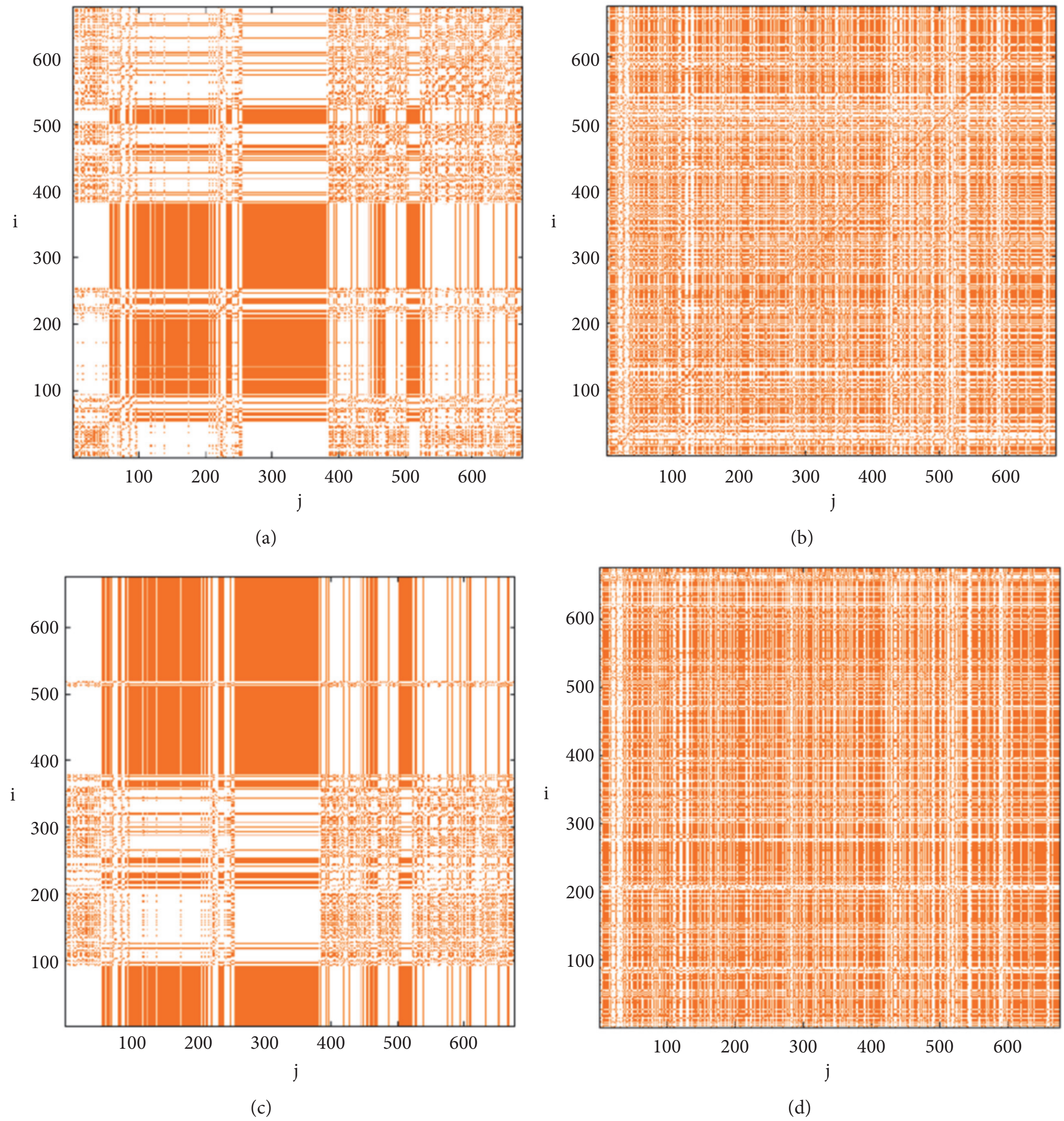


Figure 1: Recurrence plots (RP) of verbal expressions and grammar coming from an individual (Panels (a) and (b)) and dyads (Panels (c) and (d)). Panel (a) shows a RP with a delay of 1 and an embedded dimension equal to 1, in which it is possible to observe a diagonal line and coloured squares that show repetitions—in speech—of certain grammatical structures (e.g., verb, pronoun, adjective, article, adverb, among others) while the individual was interacting communicatively. Panel (b) shows a RP in which the original verbal expressions were randomized (reshuffled). Randomization destroyed the sequences and, therefore, the coherence with which the behaviours was appearing while the interaction was taking place. Thus, the RP represented by Panel (b) shows a random pattern of behaviours, in which predictability is very low, there is maximum entropy, and there is no system stability at all. Panel (c) shows a RP generated from a dyadic interaction in which C-RQA was applied. This RP and its randomized version (Panel (d)) have a characteristic that differentiates them from the RPs in panels (a) and (b). This is because the diagonal identity line is not present. Being two systems that interact, the diagonal line of identity tends to disappear.

RQA and C-RQA have been applied to detect recurring features and patterns of complex dynamical systems, which result from one or two signals interacting over time [38, 43, 48]. In psychology, such signals can be fluctuations in gait, postural changes, eye movements, or informational patterns, such as syntactic structures or words exchanged by two persons during a communicative interaction. In fact, there is a large corpus of evidence in which these nonlinear techniques have been used to analyse postural fluctuations [42], conversational interaction between caregiver and child [34, 51, 52], coupling of time series of verbalizations and gestures [50], and reading comprehension [53]. Additionally, through these analyses, interpersonal coordination has been characterized in terms of coupling of eye movements [42], body movements [41, 54], child behaviour and sleep [55], patterns of aggression [29], minimal and effective forms of coordination during the dialogue [4], and early language development [46, 47].

Even when RQA and C-RQA have been used in diverse contexts of communicative interaction, until now no research has been aimed at studying the communicative interaction of standardized routines with children, such as the Strange Situation. The implementation of Ainsworth's Strange Situation is organized in a very systematic and interesting way, and new techniques can help researchers to examine its temporal organization. Even though the main goal is to define the kind of attachment pattern of the infant, it is equally important to know how verbal expressions and motor behaviours are unfolded, and whether the structure observed in such variables can be used to estimate how traces of synchronization emerge among the individuals present during the evaluation.

Based on this background, our research aimed at analysing the unfolded verbal and motor behaviours among the participants of the Strange Situation (caregiver, child, and stranger), and to estimate, in reliable terms, the structure of these behaviours. The questions that we intend to answer are: What are the structural indicators of these behaviours that allow establishing traces of synchronization between the actors of the Strange Situation? What values do recurrence measures adopt in the behaviours of each individual and dyad (caregiver-child, stranger-child, and caregiver-stranger)?

2. Materials and Methods

Before implementing this research, the protocol was reviewed and approved by the University's Institutional Review Board (IRB # 1161533 and IRB # 1130773).

2.1. Participants. Two female infants, 14- and-18-month old, with their respective biological mothers, were recruited for this research. Both mothers were married and had completed undergraduate studies, and, according to their income, they were classified as middle class. The "strangers" were two clinical psychologists, 25 and 30 years old each. Both specialists were trained and certified in the use of the protocol of the Strange Situation. Before carrying out the study, each mother-caregiver read and signed the informed consent that was explained in detail by the researchers in charge of the study. Clinical psychologists were randomly assigned as evaluators when the procedure of the Strange Situation was administered. The sessions were recorded in a Gesell room equipped with high-resolution cameras and microphones.

2.2. Procedure

(1) Evaluation with Strange Situation Protocol. Following the protocol proposed by Ainsworth and collaborators [32], the assessment took about twenty minutes, organized in eight episodes that combined the separation and the reunion of the infant and the caregiver. The episodes lasted three minutes each. In the first episode, the caregiver enters the room with the child. In the second episode, the caregiver takes a seat while the child can interact with the toys. In this phase, the caregiver can interact with the child if the child requests it. In the third episode, the stranger enters the room, and takes a seat without interacting with the child or caregiver for a minute. The stranger then talks to the caregiver for a minute and then plays with the child for one minute. Episode four begins when the caregiver leaves the room, while the stranger stays with the child in the room. If the child is distressed, the stranger can comfort the child. In the fifth episode, the caregiver returns to the room and the stranger leaves. The caregiver knocks on the door before entering and says the name of the child. After waiting for a moment, she is free to respond to the child. She must then make the child interested in the toys and sit down again. In the sixth episode, the child is left alone in the room. In episode seven, the stranger enters the room. If the child is in distress, the stranger can comfort the child. In episode eight, the mother enters and the stranger leaves the room. The caregiver can behave in the same way as in the previous meeting. If the child is very stressed by the separations, these periods can have a shorter duration (30 seconds). The behaviours of the child observed during the two meetings (episodes 5 and 8) are coded in four scales (Proximity and contact seeking; contact maintaining; avoidance of proximity and contact; and resistance to contact and comforting). Based on these scores and taking into account the behaviour of the child throughout the procedure, the child is classified in the category of secure attachment (B), insecure avoidant (A), or resistant insecure (C). If, during the episodes that provided contact with the mother, the child presented disorganized behaviours that disrupted the organization of their attachment relationship, the classification applied is disorganized insecure attachment (D).

(2) Analysis and Categorization of Verbal and Motor Behaviours

(2.1) Words Were Labelled with a Number by Using a Text Converter. Regardless of the language, this text converter assigns a number that is characteristic and unique to each word (http://cognaction.org/rick/ati/). The procedure was repeated twice, comparing the numbers assigned to the word sequences. The reliability in assigning numbers to each word was perfect, with a Kappa value equal to one.

(2.2) The Text Converter Does Not Analyse Verbal Expressions, Grammar in Spanish, or Any Other Type of Communicative Behaviour. The coding of these variables was implemented manually. Verbal expressions and grammar were grouped in 43 descriptors. Body movements were grouped in 59 descriptors. The labels and their descriptions are provided in Tables 1 and 2. Two trained researchers, who did not participate in the application of the Strange Situation procedure, analysed the videos and categorized the behaviours of caregivers, strangers and children. These researchers were blind to the children's attachment pattern. Verbal expressions, babblings

Table 1

Code	Verbal expressions and Grammar
1	Silence
2	Inarticulate language (Crying)
3	Inarticulate language (babbling)
4	Inarticulate language (Scream)
5	Article
6	Pronoun
7	Noun
8	Verb
9	Adjective
10	Adverb
11	Conjunction
12	Preposition
13	Interjection
14	Contraction
15	Adverbial phrase
16	Own name
21	Crying
22	Crying, complaint
23	Much stronger crying
31	Babbles sound "Aa"
32	Babbles sound "Ee"
33	Babbles sound "Ii"
34	Babbles sound "Oo"
41	Shouts "Aa"
42	Shouts "Ee"
43	Shout s"Ii"

and periods of silence were transcribed and coded. A similar transcription and coding was done for body movements and gestures, where each behaviour was registered according to the moment it appeared. The interrater reliability between these two researchers was estimated with a Kappa Coefficient (Table 3) during three segments. The Kappa values were highly reliable, fluctuating between 0.71 and 1.0.

Each video was divided into a discrete number of events. There were 676 events for Video 1 and 400 for Video 2. For each participant in the Strange Situation (child, caregiver, and stranger) verbal expressions and grammar, as well as body movements were maintained in the order in which they appeared. For each participant, three files were extracted with the original time series of the three types of variables. For each variable, randomized time series were generated. Thus, for each child, caregiver, and stranger there were six files containing the three original series and their respective randomized series.

From a dynamic perspective it has been proposed that original series of behaviour form regular patterns, which have certain properties different from the same randomized series [6–10, 12–16]. A strategy to account for the dynamic character of the behaviour has been to compare the original series with the same randomized series [53]. This strategy has been implemented with fractal techniques, such as Detrended Fluctuation Analysis, Standardized Dispersion Analysis, and Spectral Analysis [56–58], and also applied with complexity measures such as RQA and C-RQA [13, 41]. Even when there are opinions contrary to this strategy and its assumptions [59, 60], some researchers had shown that this strategy is convergent with other procedures that have proven to be robust in demonstrating the dynamic and complex nature of cognitive and behavioural processes [61].

Figure 2 depicts an example of this manipulation in which verbal expressions were categorized. For the original series (Panel (a)), 45 consecutive events were selected in which caregiver and stranger were interacting (between event 205 and event 251). The numbers represent certain types of words (verbs, nouns, articles, pronouns, adverbs, among others). For the randomized series (Panel (b)), the words that were located between events 205 and 251 were selected, Differences between the original and randomized series can be visually detected. However, it is difficult to detect differences in series of 676 or 400 events. The same procedure was implemented with child-caregiver and child-stranger dyads. The complete string of verbal expressions and grammar was made up of 676 events for Video 1 and 400 events for Video 2. For individuals and dyads, original and randomized series were analysed by means of categorical RQA and C-RQA, respectively. From these analyses, measures of synchronization, such as determinism, maximum line, entropy, laminarity, and trapping time were estimated. Analyses were applied on original and randomized series, in order to be compared. Assuming that all communicative interactions have a dynamic structure in natural conditions, randomization should annihilate such structure. If the original and randomized series have the same value of determinism, entropy, laminarity, maximum line, and trapping time, it can be concluded that such a system has no coupling or synchronization.

Following the guidance of Dale and colleagues [51] for the implementation of RQA and C-RQA with categorical data, recurrence measures were estimated with one embedded dimension, and with delays of one lag. Unlike the analysis with continuous variables, in this case radius and delay were not estimated.

3. Results and Discussion

3.1. Categorical Recurrence Quantification Analysis for Individuals in Videos 1 and 2. The results for children, caregivers, and strangers are summarized in Table 4. It is possible to observe that the randomized and original series had the same level of recurrence. These results were expected, considering that randomized series were generated from the same data than the original data. Thus, the events that are part of the recurrence were organized in different order, but they are the same. Randomization breaks down the original structure, mainly affecting measures of determinism, entropy, maximum line, and laminarity. When the original structure of words, verbal expressions and grammar, and body movement was shuffled, a decrease in determinism and laminarity (lower predictability) and an increase in entropy (lower values of entropy in this case) were expected. These results, as predicted, were clearly observed in the words,

Table 2

Code	Body Movements
1	Silence
2	Takes toy 1
3	Takes toy 2
4	Takes toy 3
5	Takes toy 4
6	Takes the paper
7	Gets up off the floor (or the chair)
8	Lightens up
9	Moves hands
10	Moves arms
11	Moves head towards the girl
12	Smiles
13	Moves head towards the stranger
14	Bends
15	Moves head affirmatively (yes)
16	Takes the girl's hand
17	Takes the girl
18	Walks
19	Exits the room
20	Enters the room
21	Kisses the girl
22	Sits the girl on the floor
23	Touches the girl's head
24	Hugs the girl
25	Takes toys 1 and 3
26	Plays with toys 1 and 3
27	Drops toy or paper
28	Points forward
29	Aims towards toy 3
30	Moves the girl
31	Sings
32	Touches the girl
33	Aims for the chair
34	Moves toy 1
35	Moves toy 2
36	Moves toy 3
37	Bites toy 1
38	Bites toy 3
39	Hits toy 1
40	Hits toy 3
41	Drops toy 1
42	Drops toy 2
43	Drops toy 3
44	Picks up toy 3
45	Moves torso forward
46	Moves torso towards the mother
47	Crawls towards the mother
48	Raises hands to the mother
49	Moves torso towards stranger
50	Hugs the mother
51	Takes the mother's hand

Table 2: Continued.

Code	Body Movements
52	Touches toy 2
53	Moves leg
54	Crawls
55	Touches toy 4
56	Plays with toys 1 and 4
57	Plays with toy 4
58	Aims for toy 3
59	Takes toys 1 and 3

Table 3: Kappa values of interrater reliability.

	Ca			Ch			St		
	Segment 1	Segment 2	Segment 3	Segment 1	Segment 2	Segment 3	Segment 1	Segment 2	Segment 3
Verbal Expressions and Grammar									
Video 1	1*	1*	.99*	1*	1*	1*	.98*	1*	1*
Video 2	1*	1*	1*	1*	1*	.94*	.98*	1*	1*
Body Movements									
Video 1	.91*	1*	1*	.91*	1*	1*	1*	1*	1*
Video 2	1*	1*	.97*	1*	1*	.87*	.71*	1*	1*

Note: Ch = child; Ca = caregiver; St = stranger; $^{*}p < .0001$.

Table 4: RQA measures for individuals in Videos 1 and 2.

			Recurrence		Determinism		Entropy		Maximum Line		Laminarity	
	Variables	Unit	Orig	Ran	Orig	Ran	Orig	Ran	Orig	Ran	Orig	Ran
Video 1	String of Words	Ch	75.51	75.51	92.13	92.2	3.49	3.12	130	60	0.98	0.99
		Ca	51.41	51.41	95.64	77.43	3.96	1.9	130	6	0.92	0.72
		St	19.51	19.51	88.64	33.72	4.02	0.71	153	11	0.97	0.82
	Verbal Expressions and Grammar	Ch	75.22	75.22	92.61	94.44	3.39	3.19	69	43	0.98	0.99
		Ca	53.78	53.78	96.53	80.12	3.73	2.24	126	10	0.82	0.63
		St	24.65	24.65	80.6	38.23	3.25	0.88	155	13	0.93	0.84
	Body Movements	Ch	53.41	53.41	80.2	78.32	2.22	1.9	10	10	0.86	0.86
		Ca	43.39	43.39	73.39	68.79	2.71	1.55	37	8	0.75	0.81
		St	57.44	57.44	84.41	83.95	3.42	2.33	57	26	0.94	0.96
Video 2	String of Words	Ch	80.84	80.84	95.31	96.04	4.23	3.58	173	25	0.96	0.97
		Ca	23.31	23.31	85.96	40.95	3.48	0.89	63	11	0.98	0.93
		St	40.18	40.18	94.64	59.67	3.95	1.7	60	6	0.93	0.66
	Verbal Expressions and Grammar	Ch	82.6	82.6	95.63	97.01	4.4	3.6	172	32	0.96	0.98
		Ca	26.83	26.83	78.18	47.23	3.09	1.2	64	13	0.98	0.91
		St	43.64	43.64	91.82	69.3	3.95	1.76	62	7	0.81	0.54
	Body Movements	Ch	37.71	37.71	68.81	66.52	1.74	2.68	12	12	0.92	0.93
		Ca	32.67	32.67	58.71	56.79	2.64	1.34	33	15	0.85	0.88
		St	61.42	61.42	87.52	86.58	3.37	2.44	38	14	0.92	0.94

Note: Ch = child; Ca = caregiver; St = stranger.

verbal expressions, and grammar of caregivers and strangers, while in children the levels of determinism, laminarity, and entropy tended to remain constant. In relation to the body movements displayed during the Strange Situation, adults showed slight increases in determinism levels and decreases in entropy and maximum line levels. In contrast, the percentage of determinism in children tended to remain stable, and entropy, especially in Video 1, tended to maintain its values, while in Video 2, a decrease was not as noticeable as in the case of adults.

Based on determinism and laminarity, it is possible to establish that communicative behaviours of caregivers and

Table 5: Categorical CRQA measures for dyads in Videos 1 and 2.

Variables	Dyad	Recurrence Orig	Recurrence Ran	Determinism Orig	Determinism Ran	Entropy Orig	Entropy Ran	Maximum Line Orig	Maximum Line Ran	Laminarity Orig	Laminarity Ran	Trapping Time Orig	Trapping Time Ran
Video 1 String of Words	Ch-Ca	62.07	62.07	93.81	85.51	3.92	2.37	131	6	97.8	98.8	18.13	10.53
	Ch-St	37.89	37.89	90.78	59.74	3.82	1.32	131	12	97.4	82.7	35.33	3.87
	Ca-St	31.39	31.39	92.46	52	4.22	1.12	131	8	96.8	82.2	35.19	3.87
Video 1 Verbal Expressions and Grammar	Ch-Ca	62.49	62.49	95.31	87.22	3.72	2.6	70	11	98	99.3	18.81	10.7
	Ch-St	38.06	38.06	91.66	55.53	3.75	1.12	70	13	97.4	88	38.43	3.82
	Ca-St	34.46	34.46	90.06	52.38	3.83	1.16	128	11	90.3	80.9	26.52	3.76
Video 1 Body Movements	Ch-Ca	47.87	47.87	76.83	73.24	2.5	1.78	9	8	87.5	86.9	3.89	3.66
	Ch-St	54.89	54.89	83.46	81.07	2.68	2.12	9	10	93.4	95.3	12	5.6
	Ca-St	49.45	49.45	78.85	76.29	3.07	1.87	39	10	93.2	95.1	12	5.6
Video 2 String of Words	Ch-Ca	42.95	42.95	90.96	67.75	3.98	1.57	64	12	96.2	97.3	16.6	8
	Ch-St	56.79	56.79	95.12	77.8	4.31	2.33	61	6	94.5	67.6	23.57	2.62
	Ca-St	30.43	30.43	90.42	49.83	3.85	1.2	61	7	94.8	67.8	23.57	2.62
Video 2 Verbal Expressions and Grammar	Ch-Ca	42.74	42.74	91.16	67.24	3.96	1.85	65	14	96.5	98.5	15.9	8.3
	Ch-St	58.32	58.32	95.28	83.17	4.47	2.31	63	7	95.4	62.5	24	2.44
	Ca-St	33.5	33.5	85.63	56.7	3.5	1.45	64	5	90.4	59.5	19.56	2.44
Video 2 Body Movements	Ch	34.52	34.52	64.77	61.26	2.2	1.44	13	13	91.7	92.6	5.13	4.24
	Ca	47.67	47.67	79.92	76.45	2.34	1.92	13	13	92.1	94.4	13.56	5.43
	St	44.45	44.45	71.43	71.39	3	1.78	40	14	91.9	94	13.49	5.43

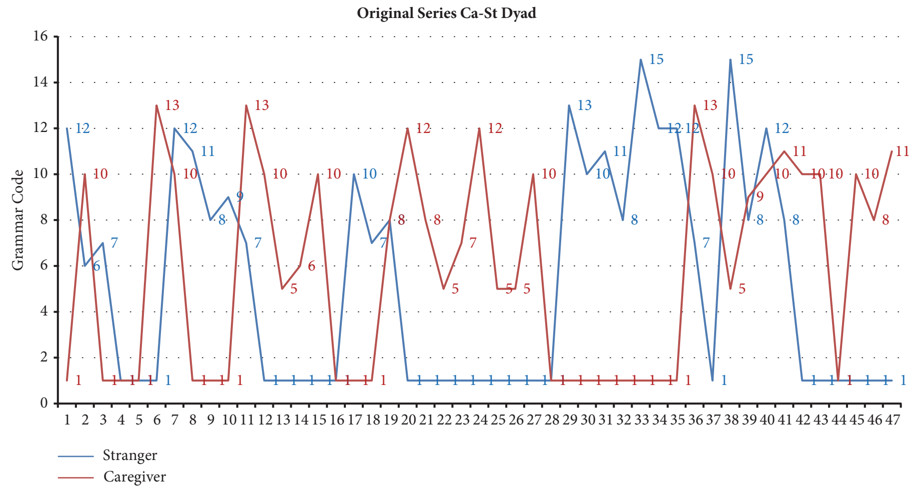
Note: Ch-Ca = child-caregiver dyad; Ch-St = child-stranger dyad; Ca-St = caregiver-stranger dyad.

strangers had higher levels of synchronization with themselves compared with communicative behaviours of children. That is to say, the initial structure of verbal and motor behaviours was a strong predictor of subsequent behaviours. On the other hand, the decrease in entropy and maximum line indicated that there was a structure or pattern in the way behaviours were organized in natural conditions. And this pattern was different from a pattern of random organization.

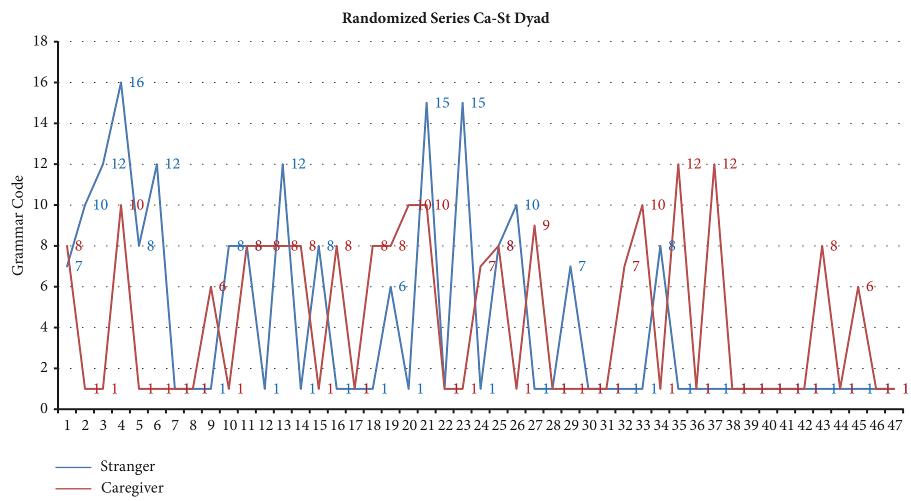
3.2. Categorical Cross-Recurrence Quantification Analysis for Dyads in Videos 1 and 2. The results for dyads in Videos 1 and 2 (see Table 5) partially replicated the values observed with individuals. For string of words, verbal expressions, and grammar, the most notorious changes were observed at the level of determinism, entropy, maximum line, and trapping time, with the original time series having higher values than the randomized series. In contrast, for body movements, changes were detected in entropy and, to a lesser extent, in maximum line and laminarity. In the three dyads, the entropy levels were higher in the original series than in the randomized series, while only in the caregiver-stranger dyad the maximum line of the original series was greater than that of the randomized series. In verbal expressions, the dyads presented values that allow us to assume a degree of synchronization. However, in terms of motor behaviour, the caregiver-stranger dyad was the only one that showed slight signs of synchronization.

Our findings indicate at least three relevant aspects. Verbal and motor behaviours revealed different degrees of synchronization [5, 11]. Words, verbal expressions, and grammar had more clear-cut indicators of synchronization and structure than body movements [43]. Likewise, individuals involved showed diverse degrees of synchronization with themselves. Both adults, caregiver and stranger, expressed better indicators of such internal coupling than infants. Finally, the synchronization indicators appeared clearly in all dyads, even when the caregiver-stranger dyad presented better indicators of coupling than the dyads where the infants were involved. The communicative interaction is a multidimensional phenomenon, in which a series of variables operating at different time scales are intertwined [44]. The analysis techniques used by us reduced the multidimensionality to the two dimensions present in the recurrence plot [39, 41, 48]. Verbal behaviours were expressed on a different time scale than motor behaviours. These verbal behaviours were a better example of the dynamic present in the Strange Situation. The dynamic was observed more clearly in the verbal behaviour of caregivers and strangers, especially when they were together in a dyad.

3.3. Comparison of Means between Groups Segmented by Communicative Behaviours, Individuals, and Dyads. Based on the recurrence measures obtained from both videos, we proceeded—in heuristic terms—to compare the original and randomized series with a Wilcoxon signed-rank test, a nonparametric test for related samples. The first comparison was segmenting by type of communicative behaviour (string of words, grammar, and body movements). In this case, the recurrence measures from individuals and dyads were grouped to estimate an average. The second comparison was among individuals (child, caregiver, and stranger). Finally, the third comparison was segmenting by dyads (child-caregiver, child-stranger, and caregiver-stranger). In both case, for individual and dyads, recurrence measures from



(a)



(b)

FIGURE 2: Panels (a) and (b) show the sequence of words that have been classified according to their grammatical function. In this segment of 47 events, only 12 categories appear. 1 = silence, 5 = article, 6 = pronoun, 7 = noun, 8 = verb, 9 = adjective, 10 = adverb, 11 = conjunction, 12 = preposition, 13 = interjection, 15 = adverbial phrase, and 16 = own name. Grammar observed in original series (Panel (a)) shows typical patterns of communicative interaction between caregiver and stranger. This typical pattern is cancelled when original time series are randomized (Panel (b)).

string of words, grammar and verbal expressions, and body movements were clustered to estimate their respective average.

As described in Figure 3 (Panels (a), (b), (c), and (d)), for the string of words the original series had a significantly higher percentage of determinism (Z = -2.82, p = .005), entropy (Z = -3.06, p = .002) and maximum line (Z = -2.20, p = .028), and a marginally higher laminarity (Z = -1.65, p = .09) than in the randomized series. The same trend was observed with verbal expressions and grammar (Panels (e), (f), (g), and (f)), where the original series had significantly more determinism (Z = -2.82, p = .005), entropy (Z = -3.06, p = .002), and the maximum line (Z = -3.06, p = .002) had a marginally higher laminarity (Z = -1.65, p = .099) than the randomized series. For body movements (Panels (i), (j), (k), and (l)), the original series had higher levels of determinism (Z = -3.06, p = .002), entropy (Z = -2.51, p = .012), maximum line (Z = -2.32, p = .021), and laminarity (Z = -2.43, p = .016) than the randomized series.

In Figure 4 (Panels (a), (b), (c), and (d)), segmenting by individuals, the children in the original series presented marginally higher levels of maximum line than in the randomized series (Z = -1.83, p = .06); however no differences were detected in terms of determinism, entropy, and laminarity ($Zs \leq$ - .11, $ps \geq$ .91). For caregivers (Panels (e), (f), (g), and (h)) and strangers (Panels (i), (j), (k), and (l)), the original series showed higher levels of determinism, entropy, and maximum line ($Zs \leq$ -2.20, $ps \leq$ 0.028) than the randomized series. However, no differences were observed in terms of laminarity ($Zs \leq$ -1.58, $ps \geq$ .11).

When focusing on dyads (Figure 5), it is possible to observe that the child-caregiver dyad (Panels (a), (b), (c),

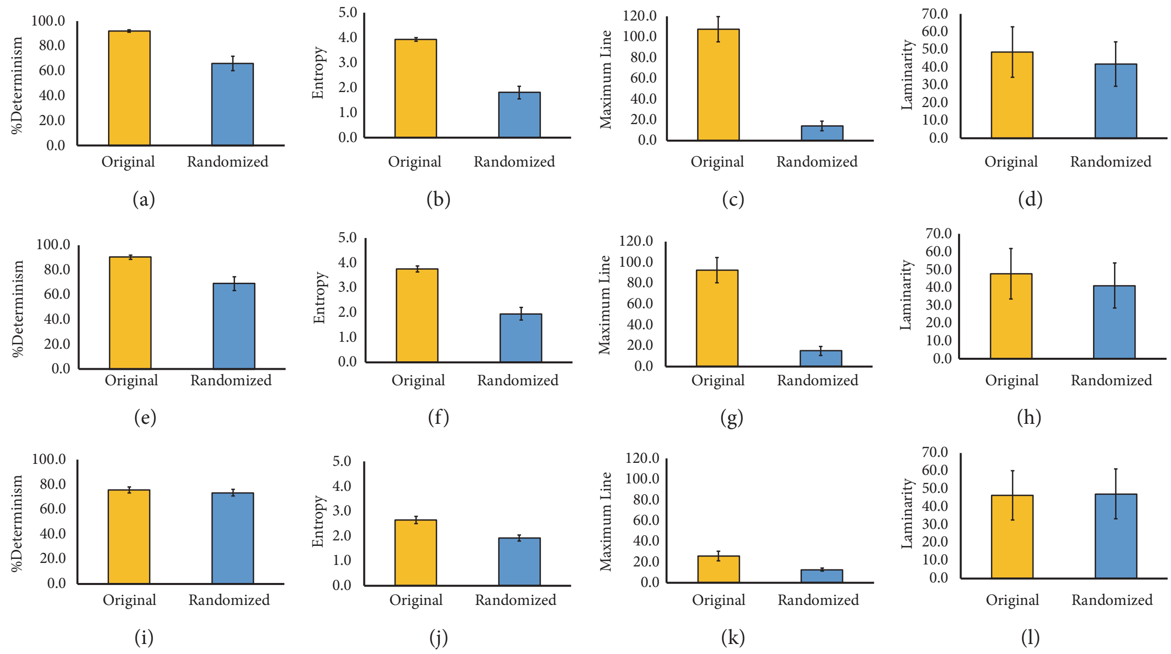


FIGURE 3: Mean and standard errors of determinism (Panels (a), (e), and (i)), entropy (Panels (b), (f), and (j)), maximum line (Panels (c), (g), and (k)), and laminarity (Panels (d), (h), and (l)), segmenting by words, verbal expressions and grammar, and body movements.

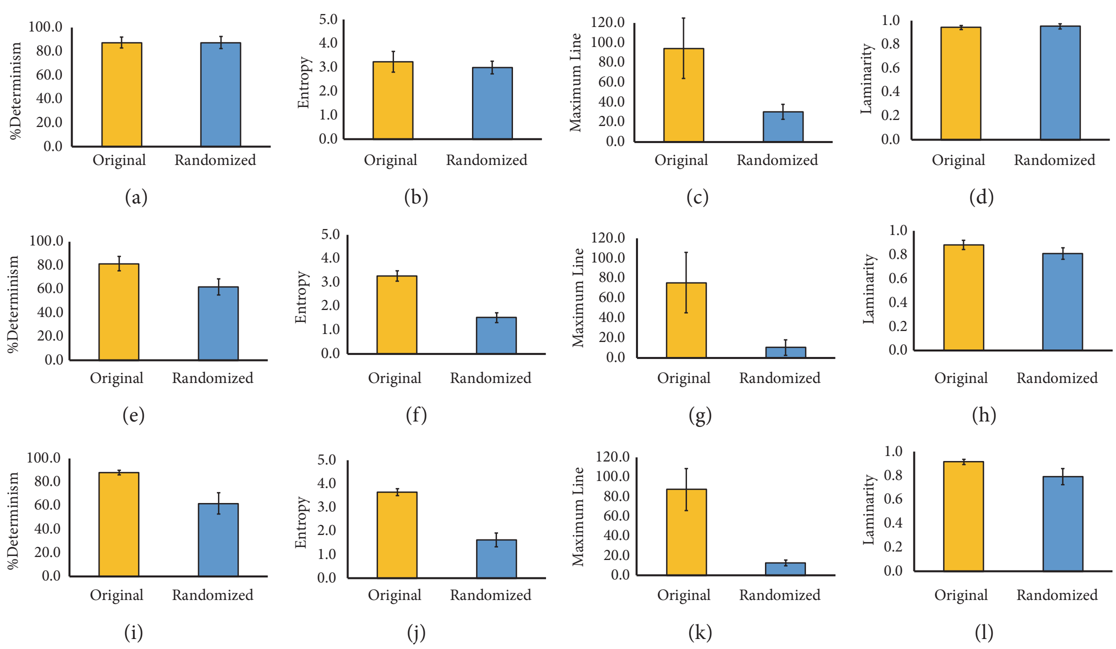


FIGURE 4: Mean and standard errors of determinism (Panels (a), (e), and (i)), entropy (Panels (b), (f), and (j)), maximum line (Panels (c), (g), and (k)), and laminarity (Panels (d), (h), and (l)) when segmenting by individuals (child, caregiver, and stranger).

(d), and (e)) in the original series had significantly more determinism, entropy, maximum line, and trapping time than in the randomized series ($Zs \geq$ -2.21, $ps \leq$ .03), but no difference was observed in laminarity. The caregiver-stranger dyad (Panels (l), (m), (n), (o), and (p)) and child-stranger dyad (Panels (f), (g), (h), (i), and (j)) showed similar trends with the original series expressing higher levels of determinism, entropy, and trapping time (Zs = -2.21, ps = 0.03), as well as a marginally higher maximum line (Z = -1.75, p = 0.08) than the randomized series. However, no differences were detected in laminarity (Z = -1.51, p = .12).

With this nonparametric analysis, we corroborate what was previously reported from the visual inspection summarized in Tables 4 and 5. Words and verbal expressions

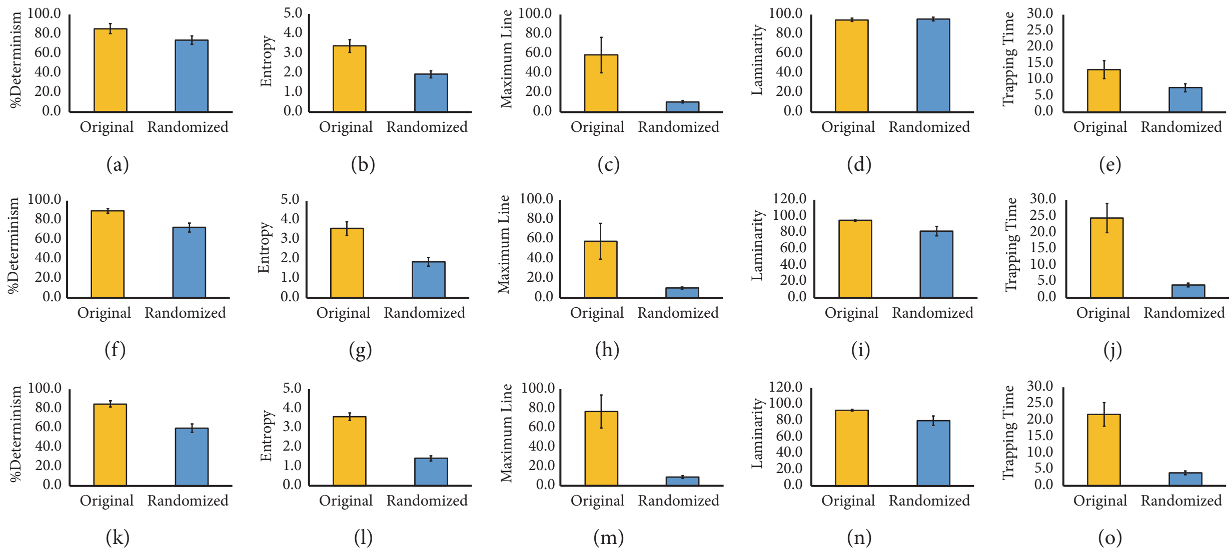


FIGURE 5: Mean and standard errors of determinism (Panels (a), (f), and (l)), entropy (Panels (b), (g), and (m)), maximum line (Panels (c), (h), and (n)), laminarity (Panels (d), (i), and (o)), and trapping time (Panels (e), (j), and (p)) when segmenting by dyads (child-caregiver, child-stranger, and caregiver-stranger).

and grammar showed a structure that resembles a typical coupling pattern. This structure was more defined and clearer than the one observed in body movements. The actors involved in the Strange Situation showed noteworthy differences among them. While children clearly showed no traces of a structure, other than that observed by chance; the behaviours of caregivers and strangers had clear traces of dynamic patterns, typical of coupled systems. Finally, all dyads presented clear synchronization indicators, especially caregiver-child dyads. It is important to note that verbal and motor behaviours expressed by children did not have elements that indicate a coupling pattern. However, when these children interacted with their respective caregivers, the communicative behaviour between them clearly expressed signs of synchronization.

4. Conclusions

The purpose of this research was to characterize the degree of structuring of behaviours in order to identify the parameters of synchronization in a protocolized communicative interaction, Ainsworth's Strange Situation [21, 27, 31–33], by analysing the unfolded verbal and motor behaviours among caregivers, children, and strangers [31–33]. These behaviours were scrutinised using a nonlinear technique named Categorical Cross-Recurrence Quantification Analysis [5, 38, 39, 41–43]. From these analyses, it was expected to estimate measures that have been used to characterize degrees of coupling between systems [44–48].

The findings showed that words and verbal expressions and grammar had clear parameters of synchronization, taking into account the fact that determinism, entropy, maximum line, and laminarity were higher in the original series in comparison to the randomized series [16]. In the case of body movements, communicative patterns showed a type of synchronization with a recurrent structure, where the initial states enabled predicting the final states of the system, but whose stability was not different from a series where the motor behaviours appear in a random manner [40, 43–48, 51]. Thus, our results indicate that verbal behaviours—in the Strange Situation—are part of a communicative phenomenon that expresses higher levels of synchronization than motor behaviours [45, 46]. This preliminary finding emphasizes that the communicative interaction has synchronization features, but these attributes are not homogeneous. If, until now, we assumed that communicative interaction—among three people interacting during a protocolized evaluation—was globally synchronized, our results suggest that some aspects have more dynamic characteristics than others.

For children, the values of determinism, entropy, maximum line, and laminarity remained constant between the original and randomized series. Thus, the structure of verbal and motor behaviours expressed for children was not different from what was to be expected if these behaviours appeared in a random manner. In contrast, for adults—caregivers or strangers—the values of determinism, entropy, laminarity, and maximum line were significantly reduced when their original series were randomized, suggesting that the original series of communicative behaviours had a synchronization pattern that was far from a random organization. This made us aware that, in a communicative interaction, not all actors involved have synchronized behaviours. However, when analysing the recurrence of two people interacting, the system itself shows traces of synchronization, even when one of the actors (in our case the children) does not show synchronization traits.

We are still blind to the attachment pattern of these two girls who participated in the Strange Situation. However, there are two possible scenarios that we conjecture. In the first one it can assumed that both infants have the same attachment pattern—regardless of whether this pattern is A, B, C, or D—and therefore the observed values indicate a similar pattern of recurrence among them as observed in our study. Another possibility is that the attachments of these infants are different (generating the possible combinations of A and B, A and C, A and D, B and C, B and D, or C and D) [31–33]. Under this scenario, the observed recurrence values (entropy, laminarity, determinism, among others) did not detect the differences that the infants manifested in their attachment behaviours or how this pattern of attachment was unfolded in the interaction with adults. So, in order to disambiguate this problem our current work is aimed at analysing more Strange Situation videos, where each of the four types of attachment patterns can be represented proportionally. Thus, this preliminary investigation can be improved with the incorporation of more children classified according the four types of attachment [21], in such a quantity that comparisons can be made in terms more robust [44]. Attachment patterns are discrete categories defined by certain behaviours. Some of them promote communicative interactions with adults, while others restrict them [30]. Therefore, it is expected that recurrence parameters tend to vary from one type of attachment pattern to another.

Our study resembles a study with small samples or two unique cases study. The nonparametric contrasts that we conducted were purely heuristic and corroborated what the tables expressed. However, the possibility of comparing means depends on having an adequate sample size. Despite this limitation, the direct observation of the recurrence parameters in the recurrence plots is an extended practice, because the means and deviations are deceptive, insofar as they can hide the temporal structure of the behaviours [2, 8, 40, 43]. Two groups could have the same mean and the same standard deviation and not show significant differences. However, they could have a different structure of variability over time. This last aspect is what the recurrence plots and RQA identify and that we have applied to Ainsworth's Strange Situation.

The Ainsworth's Strange Situation protocol is intended to study the infant's attachment pattern. In this protocol, two adults, the caregiver and the stranger, interact with the infant. However, it is also possible to observe that these adults interact with each other for a few minutes. In that sense, the interaction between the caregiver and the stranger is susceptible to be analysed in terms of verbal and motor behaviour. Considering that the central objective is to establish the attachment pattern of the infant, a rational and feasible decision could be to omit information regarding the few minutes of interaction between the caregiver and the stranger; however, we believe that it is early to make such a decision, considering that we are still estimating the weight that each actor has in the interactions that the protocol promotes. Social interactions have a dynamic character; therefore what will happen in the future is a function of what has happened in previous phases. Therefore, we suppose the interaction of these two adults in a previous phase could be an important ingredient that affects their interaction with the infant in the following phases.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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Supplementary Materials

The databases, coding matrices, and transcriptions of the interactions can be requested from Ramón D. Castillo (racastillo@utalca.cl) and (ramondanielcastillo@gmail.com). *(Supplementary Materials)*

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Research Article

Does Competence Determine Who Leads in a Dyadic Cooperative Task? A Study of Children with and without a Neurodevelopmental Disorder

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Cooperative learning is an effective means for the acquisition of academic performance. It is an established fact that collaborating members should be operating in one another's zone of proximal development to attain optimal performance. One variable that plays an as-yet unknown role in collaborative success is the leader-follower distinction. In the present study, leading and following behavior was determined by assessing rhythmical coordination of postural sway in typically developing children (n = 183) and children with a neurodevelopmental disorder (n = 106). Postural sway was measured using Nintendo Wii Balance Boards, and dyads performed a tangram task while standing on these balance boards, with the number of puzzles solved correctly serving as the measure of task performance. Irrespective of task performance, there was a consistent pattern of leading and following in typically developing dyads: the higher-ability child was in the lead. For children with a neurodevelopmental disorder, the pattern differed depending on task performance. While the patterns of low-performing dyads were comparable to those of typically developing children, high-performing dyads showed the opposite pattern; namely, the low-ability dyad member was in the lead. For interactions with children with a neurodevelopmental disorder and a low-level cognitive ability, it may be better to follow their lead, because it may result in better performance on their part.

1. Introduction

Cooperative learning refers to a method in which two or more individuals work together in small groups towards a common goal with the aim of helping one another in the acquisition of academic knowledge [1]. Its success is to a large extent affected by positive interdependence, individual accountability, positive interactions, appropriate social skills, and group processing (for a more detailed description, see [2]). Cooperative learning appears to be rather effective. Johnson, Maruyama, Johnson, Nelson, and Skon [3] reviewed 122 studies on the effects of cooperative, competitive, and individualistic goal structures and showed that cooperative groups performed better than competitive groups and individuals. More recently, Roseth, Johnson, and Johnson [4] conducted a similar meta-analysis, examining nearly 150 studies. They also found that cooperative goal structures were related to better task performance than competitive or individual goal structures.

An important factor that affects the outcome of cooperation is dyad composition. Vygotsky [5], for example, stated that the ability level of the cooperating individuals is crucial and that the determining factor for successful cooperation is that one individual is, or moves within, the other's zone of proximal development (ZPD). Vygotsky defined the ZPD as "the distance between the actual developmental level as determined by independent problem solving and the level of potential development as determined through problem solving under adult guidance or in collaboration with more capable peers" (p. 86). Vygotsky believed that the ZPD is important for cognitive growth. A child who is learning within his or her ZPD can do things with the help of a more experienced person (peer or adult) that he or she was not (yet) able to do alone. Thus, for cooperative learning to be successful, from a Vygotskian point of view, there has to be active interaction (explaining and reasoning) between individuals who differ in levels of expertise. This in turn may result in intersubjectivity or a shared understanding through discussion of different viewpoints [6, 7]. Although cooperative learning has been shown to be successful, working in Vygotsky's zone of proximal development is not the only reason for that [8]. Task performance is not just determined by cognitive ability level, but also by other factors as well. One of these factors is who takes the lead and who follows the lead of the interaction partner.

1.1. Leading-Following Behavior. Being a leader or a follower has been related to academic achievement and peer evaluations. Dingel and Wei [9] studied introductory sociology students who participated in an interdisciplinary project. In this project, they collaboratively wrote three papers in groups of four to six students. In the final week of class, students were presented with a survey, in which they were asked to indicate, among other things, whether they felt like a leader and a follower in their own group (both could be answered with yes or no). Dingel and Wei found that not only leaders had higher peer evaluations than followers, but also they received higher average grades than followers. Dunbar, Dingel, Dame, Winchip, and Petzold [10] found similar results; leaders had higher grades and higher social self-efficacy than followers.

Notwithstanding the significance of these findings, they examined leader-follower behavior at a macro level, that is, as an outcome measure. An alternative perspective is studying the behavior at a micro level by looking at the process (or dynamics) that underlies macro-level observable behavior. Wichers' [11] study provides a recent example in which micro-level patterns revealed the development of symptoms of depression. In the present study, we studied the micro-level dynamics of postural sway to provide insight into the working mechanisms that underlie leader-follower behavior in a dyadic cooperative task.

During a task in which two people have to work together to perform it, bodily movements have to be adjusted to one another. An unobtrusive measure is postural sway; it reveals the (un)conscious back-and-forward as well as left-to-right movements of an individual. The movements of one individual can entrain those of the cooperative partner in the dyad. The one who initiates the movement is called the leader and the one who follows the follower. Because all tasks require behavior and all behavior requires movement, postural sway appears to be an excellent exemplar variable to investigate the underlying pattern of cooperation and leader-follower behavior (e.g., [12]). More concretely, we aim at investigating whether leader-follower behavior is related to task performance over the course of an interaction (i.e., across time), but also whether similar or different mechanisms are at work in different populations (i.e., typically developing children and children with a neurodevelopmental disorder).

One way to analyze these micro processes over time is by means of Cross Recurrence Quantification Analysis (explained in more detail in Methods section). Guevara, Cox, van Dijk, and van Geert [13] have shown its potential for studying cooperative behavior, Leonardi, Nomikou, Rohlfing, and Rączaszek-Leonardi [14] for leader-follower behavior in mother-child interaction, and Warlaumont, Richards, Gilkerson, and Oller [15] for leader-follower behavior in typically developing infants and infants with ASD. In the next paragraph, we explain leading-following behavior in terms of rhythmical coordination.

1.2. Rhythmical Coordination. Leading and following behavior of a dyad has been studied during rhythmical coordination of bodily movements and the outcome of a cooperative interaction is related to the level of interpersonal synchrony or interpersonal coordination (e.g., [16–18]). *Synchrony* involves engaging in the same action (i.e., the spatial aspect) at (about) the same time (i.e., the temporal aspect). For example, when two people are walking side by side and their stride-intervals are the same, their behavior is synchronized. *Coordination* is about timing, the *when* (i.e., the temporal aspect), and not so much about what is being done, the *what* (i.e., the spatial aspect). For example, when two individuals are lifting a table together, it does not matter how either one of them does it, as long as they lift it at the same time. Here we focus on interpersonal coordination, that is, on the timing or rhythm of behavior.

Jaffe et al. [19] defined rhythm as "... a recurrent non-random patterning that may or may not be strictly regular" (p. 1). All motor and vocal behavior has a rhythm [20]. This rhythm reveals information about the interaction partner [21]. Coordination of (vocal) rhythms always takes place in relation to those of the interaction partner and, interestingly, the timing of preverbal dialogues appears similar to that of verbal dialogues in adults [22]. Infants are already equipped with the tools for conversation before they can talk. It is through expectancies and anticipation, knowing what the other will do in relation to what you are doing, that this kind of coordination of timing patterns (e.g., when to pause, or whose turn it is) is possible [22]. Synchronized behavior generally leads to positive effect, whereas individual rhythms that are not properly coordinated can cause a feeling of uneasiness (e.g., [23, 24]).

It is still unclear whether it is better to have high or low levels of coordination. Chapple (in [19]) argued that it is better to have high levels of coordination, whereas Gottman [25] stated that high levels of coordination are related to distress in communication. More recent work has shown that in some situations the preferred level of coordination depends on the environment or task demands [16–18], thus challenging the idea that it should be either high or low. Vink et al. [17] asked 183 dyads of primary-school children to perform a tangram task while standing on a Nintendo Wii Balance Board. The balance board recorded each child's postural sway. The results showed that task performance was better when the dyad's postural sway was loosely synchronized. Dyads that performed better had less deterministic postural sway patterns than dyads that performed worse. However, this was only the case for postural sway movement on the x-axis. According to the authors, this indicated that better task performance demanded more coordination rather than synchronization. That is, the less deterministic postural sway patterns indicated that the periods of synchronized dyadic postural sway were shorter in the better performing dyads, which may suggest that it is more important to coordinate than synchronize.

In a follow-up study, Vink et al. [18] analyzed the displacement of postural sway, instead of the separate x- and y-axis measurements used by Vink et al. [17], and they examined a different outcome measure, the level of entropy of the dyadic postural sway. Vink et al. showed that in better performing dyads the level of entropy was lower than in worse performing dyads, indicating that there was more order in better performing dyads' postural sway patterns. Combining this with the results of their previous study, Vink et al. again concluded that coordination is sometimes more important than synchronization, since better performance was indicated by more ordered, shorter periods of similar postural sway, and dyads continuously adjust their postural sway to that of their interaction partner.

Abney et al. [16] also maintained that in certain interactions it is better when dyads are more loosely coupled. They asked participants to perform a dyadic problem-solving task in which they had to create an as high as possible tower from raw spaghetti and marshmallows. One participant had control over the spaghetti, while the other handled the marshmallows. When dyads were more loosely coupled, that is, more coordinated, their performance was better. In addition, Abney et al. showed that performance also depended on the role division within each dyad. Although their results did not reach significance, they did point to the possibility that "... the emergence of role-sensitive temporal organization may be vital to effective performance in highly constrained dyadic problem solving" (p. 321).

Not everyone, however, is able to rhythmically coordinate smoothly. Individuals who suffer from a neurodevelopmental disorder, such as people with autism, have been shown to not only experience difficulties communicating [26], but, almost all of them, suffer from motor control problems, which in turn may add to synchronization problems (Pettersson, Anckarsäter, Gillberg & Lichtenstein, 2013). Tiegerman and Primavera showed that communicating was hampered to a large extent by gaze aversion (i.e., not wanting to look at other people's faces). Interestingly, imitating or synchronizing the behavior of the individual with a neurodevelopmental disorder may enhance communication; when the experimenter imitated the actions of the autistic child, there was an increase in gaze frequency and gaze duration, as opposed to when the experimenter did not imitate the autistic child's behavior.

Additional support for this idea came from Trevarthen and Daniel [27]. They observed different rhythms in the interactions between a father and his monozygotic twin daughters. At the age of two, one of the girls was diagnosed with autism. The videos that were analyzed were made when the girls were 11 months old, long before one of them was diagnosed with autism. Trevarthen and Daniel's analysis revealed that the father interacted differently with his two daughters. In the interaction with his nonautistic child a clear rhythm (i.e., coherent temporal regulation) was visible, whereas in the interactions with the autistic child this rhythm was absent. Moreover, to encourage his autistic daughter to engage in the interaction, he took the lead, whereas the interactions with his nonautistic daughter revealed more following behavior. Although this behavior feels natural to most of us, Gernsbacher [28] suggested a counter intuitive notion, namely, that children with a neurodevelopmental disorder may actually need to be in the lead and have a more capable interaction partner to follow their lead. This idea adds to Vygotsky's [5] theory, in that the more skilled individual has to position him- or herself within the less skilled individual's zone of proximal development and from there the more skilled individual should follow the lead of the less skilled individual.

Vink et al. [18] examined whether typically developing children and children with a neurodevelopmental disorder (e.g., autism and ADHD) differed in task performance and coordination of postural sway. The children had to cooperate in solving tangram puzzles, while their postural sway was recorded. As expected, the results showed that children with a neurodevelopmental disorder performed significantly worse on the tangram task than their typically developing peers. However, when studying their postural sway during this cooperative process, the entropy effect was the same in both groups: lower levels of entropy (i.e., reduced disorder of synchrony) were related to better task performance. In other words, dyads performed better when their postural sway was more coordinated. This suggests that the nature of the interaction is more important than the disorder to explain the communication difficulties. In the Trevarthen and Daniel [27] study, the problem may not have been that one child was autistic and the other was not, but a mismatch between the natural rhythms of the interaction partners in case of the interaction between the father and the autistic child. These findings led us to wonder what could account for observed differences in the outcome of a cooperative task, if it is not the level of coordination. Could it be different patterns of leading and following?

1.3. Present Study. This study addresses three questions. One, who leads and who follows in a cooperative task? Previous research has shown that more skilled people are often leaders and Hooper [8] showed that homogeneous high-ability dyads had superior performance, whereas average-ability homogeneous dyads were the poorest performers on a cooperative task. However, and related to the second question, how roles are divided may depend on task performance. Two, are leader-follower patterns related to task performance? A conjecture is that in better performing dyads the more skilled child is the follower, whereas in worse performing dyads the more skilled child is the leader. Three, is there a difference in leader-follower patterns between typically developing children and children with a neurodevelopmental disorder? As Leonardi et al. [14] showed, typically developing children may not be in need of follower over the course of their development, whereas children with a neurodevelopmental disorder may profit from a more skilled follower. We will therefore investigate whether leader-follower behavior differs between typically developing children and children with a neurodevelopmental disorder when they cooperate on a cognitive task.

2. Method

2.1. Participants. Children were randomly assigned to a same-sex dyad, because only same-sex (not mixed-sex) dyads perform better together than they do individually [29]. Not all dyads that participated were included in the study. Reasons for exclusion were either technical failures with data recording or an uneven number of children in a classroom, which led to one child participating in two dyads or in a dyad that was not same-sex. The group of typically developing children consisted of 183 dyads attending regular-primary education (M_{age} = 10;8 years, *SD* = 1;00, range: 8-13, 95 boys and 88 girls). The group of atypically developing children consisted of 106 dyads attending special-primary education (M_{age} = 10;10, *SD* = 1;3, range: 8 – 13; 74 boys and 32 girls). Note that, in Netherlands, inclusive education is not yet fully implemented. A large group of children with special needs are referred to special-primary education. They do not necessarily have an official DSM diagnosis (although many of them do), but all of them show behavior that is reminiscent of a developmental disorder. Due to the large diversity within this group, it is difficult to draw conclusions about each of the disorders that are present. Therefore, we chose to look at this group as a group of children with a developmental disorder (i.e., the commonality) and how this group differs from its typically developing counterpart.

Letters were sent to a large number of Dutch regular and special-primary schools to request participation. After two weeks, schools were asked whether or not they wanted to participate. Schools that responded positively received additional information by email, including a letter for the parents in which they were informed about the study and asked for permission for their child's participation. A passive consent procedure was followed.

We did not seek approval from the Ethics Committee for conducting the research related to the research project 'Synchronizing to Learn and Like.' The reason was that, within the Behavioural Science Institute, it was not customary to do so at the time this research was conducted. Only research using invasive methods required approval from the Ethics Committee. The present study was noninvasive and did not pose any threats to the participants in whatever possible way.

2.2. Materials and Procedure

2.2.1. Nintendo Wii Balance Boards. Postural sway of both dyad members was recorded using two Nintendo Wii Balance Boards (WBBs; Nintendo, Kyoto, Japan). The WBB is a reliable, easily moveable, and inexpensive alternative to the less portable and more expensive force platforms often used in clinical settings [30, 31]. A custom-made Windows-based program recorded the two WBBs simultaneously (Voogt, TSG-FSW, Radboud University, The Netherlands). Sampling rate was set at 100 Hz and the collected data provided information about postural sway in both the medial-lateral (x-axis) and anterior-posterior (y-axis) direction.

2.2.2. Tangram Task. A tangram puzzle consists of seven pieces: two large triangles, one medium triangle, two small triangles, a square, and a rhomboid (see Figure 1). These pieces can be used to create all kinds of figures. The figures that the dyads had to recreate were printed on A4 paper.

The experiment took place at school, in a room in which a table was present. Table height was adjusted to the needs of each of the dyads. The children performed the task both individually and cooperatively. Prior to the individual task, the children were verbally informed by the experimenter who demonstrated how the task was to be performed using an example tangram puzzle. The children had to lay the tangram pieces on top of printed figures on A4-paper. There were three different sets consisting of 18 tangram puzzles each: sets A and C were used for the individual part, set B for the cooperative part.

During both the individual and cooperative parts of the task, children had 10 minutes to recreate as many tangram puzzles as possible. The number of puzzles correctly solved when they performed the task individually served as the pretest measure. This pretest measure was used to determine which of the dyad members was the more competent one. The number of puzzles solved correctly when they performed the task together served as the measure for the cooperative task score. During these 10 minutes, they stood on the WBB, and their postural sway was monitored. Children were allowed to move, as long as they did this on the WBB. During the individual part the WBBs were approximately 70 centimeters apart, while during the cooperative part they were approximately 10 centimeters apart. After finishing a puzzle, the researcher checked whether it was correct. If so, the child or dyad was allowed to continue to the next puzzle, otherwise they were asked to keep trying. Only when a child or dyad made many unsuccessful attempts or became very frustrated were they allowed to skip a puzzle. After 10 minutes, children were told to stop and asked to step off of the WBB. The number of correctly recreated puzzles was the task performance score. After finishing the experiment, as a token of gratitude for their participation, the children were given a small present (e.g., a pen or pencil).

2.3. Data Preparation and Analysis

2.3.1. Cross Recurrence Quantification Analysis. Data reduction was first performed on the original data, given the computational intensity of the analyses. We down sampled the data to 5 Hz (the original data was sampled at 100 Hz), resulting in time series of approximately 3,000 data points per dyad. Next, the Displacement (Displ) scores were calculated from the X-Y coordinates. Equation (1) shows how this was done:

$$\mathrm{Displ}_t = \sqrt{\left(X_{(t+1)} - X_t\right)^2 + \left(Y_{t+1} - Y_t\right)^2}, \tag{1}$$

where X represents the raw medial-lateral measure and Y the anterior-posterior measure of postural sway.

The Cross Recurrence Quantification Analyses (CRQA) on the Displ data were analyzed in Matlab® (Mathworks Inc., 2012) using the Cross Recurrence Plot (CRP) Toolbox (http://tocsy.pik-potsdam.de; [32]) and *casnet* [33], a package for the R language [34]. To perform CRQA, the shared phase

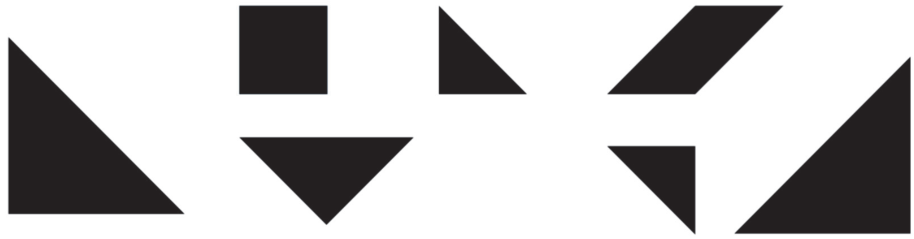

Figure 1: Tangram puzzle pieces.

space of the dyadic time series was reconstructed using the method of time-delayed embedding [35]. To determine an appropriate delay, the Average Mutual Information (AMI) was calculated over increasing time lags. The time lag where the first local minimum (hence, the point where the time series reveal an optimum amount of unique information) appeared was chosen for the reconstruction (5 data points). Next, the embedding dimension (7) was determined by a first local minimum of False Nearest Neighbors (FNN; cf. [36]). The radius (i.e., the area in the shared phase space where revisiting trajectories are considered recurrent) was allowed to vary within each dyad, so that the recurrence rate within each dyad was exactly 5% (cf. [37]). These parameters were used to optimize the reconstruction. However, as Riley et al. [36] stated, for recurrence analyses on postural sway data, the choices for time lag and embedding dimension are not crucial, but a way to optimize the phase space reconstruction. Before analysis, the time series were rescaled to the maximum phase space diameter [38]

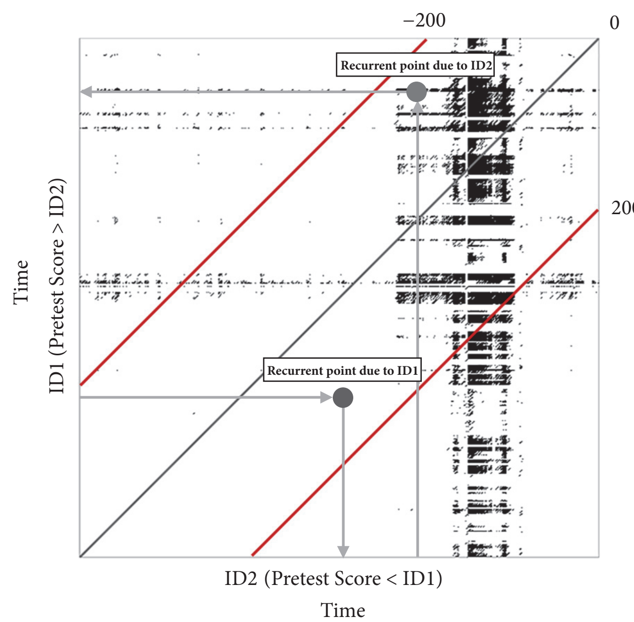

Figure 2: A Cross Recurrence Plot of Dyad 47 during the cooperation condition.

2.3.2. Descriptive Analysis of Leading-Following Behavior in Postural Sway. From the CRQA analyses we extracted for each dyad the diagonal-wise recurrence rate (see [39], for a detailed description). For each dyad, a diagonal recurrence profile (DRP) was obtained within a window of 200 samples above and below the LOS (i.e., 40 seconds, 5 Hz). A DRP says something about "... how much coordination occurs within a "window" of relative time between participants" and "... the DRP allows us to explore similarities in patterns of movement that are independent of *absolute* time while revealing patterns of *relative* time" [40, p. 6]. We chose to look at the determinism measure (DET) within the diagonal profile, which is the percentage of recurring points that lie on a diagonal line in the Cross Recurrence Plot (CRP). This measure tells us something about the nature of the coupling between the two time series as it records recurring shared trajectories that last longer than just 1 point in time. In short, a DRP can tell us something about leading and following behavior in the interaction dynamics of postural sway that evolved during cooperative problem solving.

To make sure that all DRPs are comparable, we chose to place the dyad member that performed best on the pretest on the left side (the y-axis in the Cross Recurrence Plot, see Figure 2) and the dyad member that made less puzzles correct on the right side of the plot (the x-axis in the CRP). DRPs should be interpreted as follows (see also Figures 2 and 3). If the determinism peak is left of the middle, the worse performing dyad member was in the lead and the better performing dyad member followed. If the determinism peak is right of the middle, the better performing member was in the lead and the worse performing dyad member followed. The distance from the middle to the peak indicates the time lag between the recurrent patterns: the larger the distance is, the longer it took the follower to follow the leader's movement. When the peak is approximately in the middle, there is near-synchronized behavior, indicating that each member did the same thing at about the same time and there was no clear leader or follower. A peak on both sides indicates bi-directionality or turn taking in the interaction. Sometimes the better performing dyad member was in the lead and sometimes the worse performing dyad member was in the lead.

Figure 2 presents a Cross Recurrence Plot of a dyad during cooperation. ID1 on the y-axis is the child with a higher pretest score than ID2, who is on the x-axis. Recurrent points below the line of synchrony (LOS, the matrix diagonal) are due to ID1: the recurring value first occurred in the time series of ID1 and later in the time series of ID2. Similarly, recurrent points above the LOS are due to ID2. The DRP based on determinism (DET) is constructed by calculating the proportion of recurrent points that form a line for each matrix diagonal contained in the window around the LOS (between the red lines). DET values from diagonals above the LOS are displayed on the left side of the DRP (window range -200:0 in Figures 3 and 4), values from diagonals below the LOS are displayed on the right side in the DRP (window range 0:200 in Figures 3 and 4).

The DRPs of individual dyads were grouped based on their cooperative task performance: those that scored low (0%-25% percentile), average (25%-75% percentile), and high (75%-100% percentile); within these percentile groups the DRPs were aggregated across participants in the regular and special education groups separately. The low-scoring dyads finished 3-6 puzzles, the average group finished 7-10 puzzles, and the high-scoring group finished 11-15 puzzles. Note that for the children attending special-primary education, only five dyads finished 11-15 puzzles.

The aggregated DRPs are shown in Figure 4. These are so-called *centroids* obtained by using the shape extraction function algorithm in R package *dtwclust* [41]. The algorithm uses a shape-based distance metric on coefficient-normalized cross-correlation functions to generate the mean shape, or centroid profile from set of different time series (cf. [42]). The spiky grey lines in the upper part of Figure 4 are the extracted mean profile centroids, which were smoothed for clarity of presentation (loess, span = .2). In addition, the bottom two rows represent the mean score + 95% bootstrapped CI. We chose to look at DET (z score, represented on the y-axis), as this measure tells us something about the long-range recurrent trajectories in an interaction and not only about occasional steady point similarities.

2.3.3. Permutation Test of Group Profile Differences. The blue vertical lines in Figure 4 represent significant differences between the regular and special education centroids. A p value for the observed difference can be constructed by conducting a permutation test in which the temporal order of values in each time series is resampled many times, after which difference scores are computed on the resampled series. For each percentile group, the extracted centroids in the DRP were resampled 9999 times using the method of random block size resampling implemented in function *tsboot* from R package *boot* (v. 1.3-20, [43]). Because observed time series are autocorrelated, robust resampling is often achieved by defining blocks (bins) that cover the time series and by randomizing those blocks while keeping the sequential order of values within a block as observed [44]. In our permutation analysis block sizes were variable and drawn from a geometric distribution with a mean of 5 (the partial autocorrelation function of the series of observed differences yielded significant correlations up to 4-6 lags). The permutation test evaluates the rank of the observed difference score among the 9999 resampled difference scores for each time point (i.e., ranging from 1 to 10,000). A p value can be calculated by dividing the number of difference scores that are equal to the observed difference or more extreme, on the number of values in the distribution. If the observed value would have had rank 1, the associated p value would be .0001. The alpha level was adjusted for multiple comparisons from .05 by a factor of 3, because the 3 analyses for each percentile group are based on subsets of the independent samples from each school type. The blue lines in Figure 4 correspond to observed differences with a p value $< .017$.

3. Results

Table 1 presents the descriptive statistics of the task performance scores of the individuals and dyads, for both the typically and atypically developing children. The table reveals that dyads performed better than individuals and that typically developing children performed better than children with a neurodevelopmental disorder.

Next, we describe the results of the leader-follower analyses. We chose to use the individual task performance to distinguish between the individuals making up a dyad. Figure 4 shows the leader-follower results of the three performance groups (low, average, and high), distinguishing between typically developing children (i.e., the lighter line) and children with a neurodevelopmental disorder (i.e., the darker line). Below each graph the number of puzzles corrected by the dyad and by each dyad member individually are plotted (P1 is the high-performing dyad member; P2 is the low-performing dyad member). As the scores below the graph show, both groups did not appear to differ a lot on individual scores and cooperative scores.

For low-performing dyads, there was a similar pattern for children attending regular-primary education and children attending special-primary education. For both groups, the best performing child was in the lead, while the child who performed lowest on the individual task was the follower. The peak, however, was far to the right, indicating that it took some time before the worse performing child followed the lead of the better performing child.

For average-performing dyads, the pattern appeared quite similar to that of the low-performing dyads, but only for the children attending regular-primary education. Here, again, the better performing child was in the lead. The peak moved closer to the center, indicating that leading-following took place closer in time than the lowest performing group. For the special education group, however, a different pattern was observed. The peak had moved slightly to the left side of the graph, indicating that the worse performing child was in the lead. In addition, the leading-following pattern took place closely in time, near the line of synchrony. Thus, the postural sway patterns in average-performing dyads of special education children were nearly synchronized.

For high-performing dyads, the results of the groups were opposite. Among children attending regular-primary education, the better performing child was still the leader. The peak had shifted even more towards the LOS, indicating that there was less of a delay between leading and following. Among children with a neurodevelopmental disorder, however, the peak had moved to the left side of the graph, indicating that the best performing dyads were led by the low-performing dyad member.

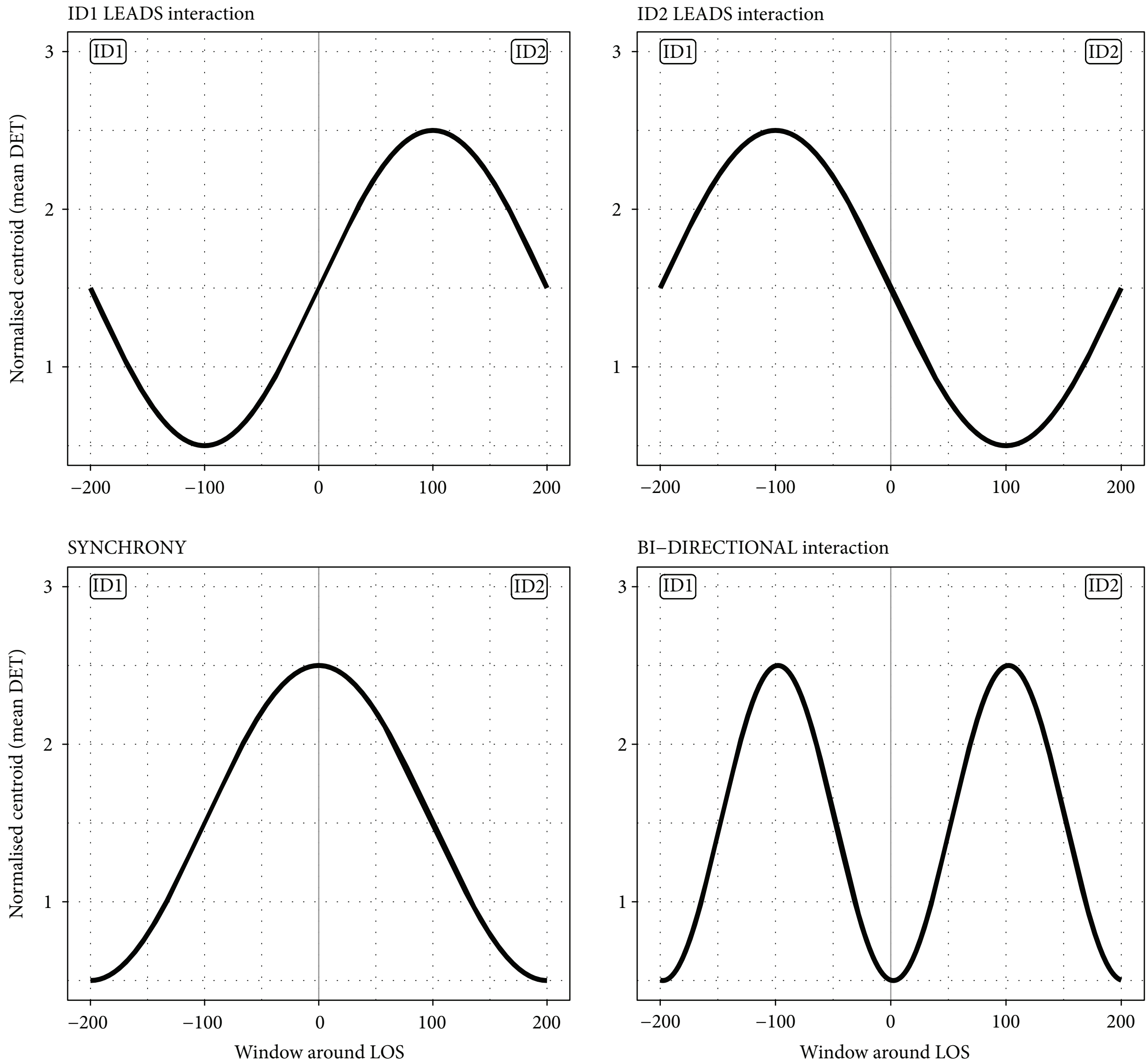

Figure 3: Examples of ideal diagonal-wise recurrence profiles showing possible leading-following patterns.

Table 1: Descriptive statistics of individual and cooperative task performance for children attending regular and special primary education.

	N	*M*	*SD*	Min	Max
Regular Education					
Individually	366	5.73	2.29	0	14
Cooperation	183	9.17	2.55	5	15
Special Education					
Individually	212	3.97	1.93	0	9
Cooperation	106	6.75	1.81	3	13

To summarize, leading-following among children attending regular-primary education remained quite similar in all three ability groups, the better performing dyad member was in the lead. What changed was the fact that across groups, moving from low- to high-performing dyads, there was a decrease in the delay between the leader and follower's postural sway. For children attending special-primary education, there was a clear difference between the three ability groups. In the low-performing dyads it was clearly the better performing dyad member that was in the lead. The exact

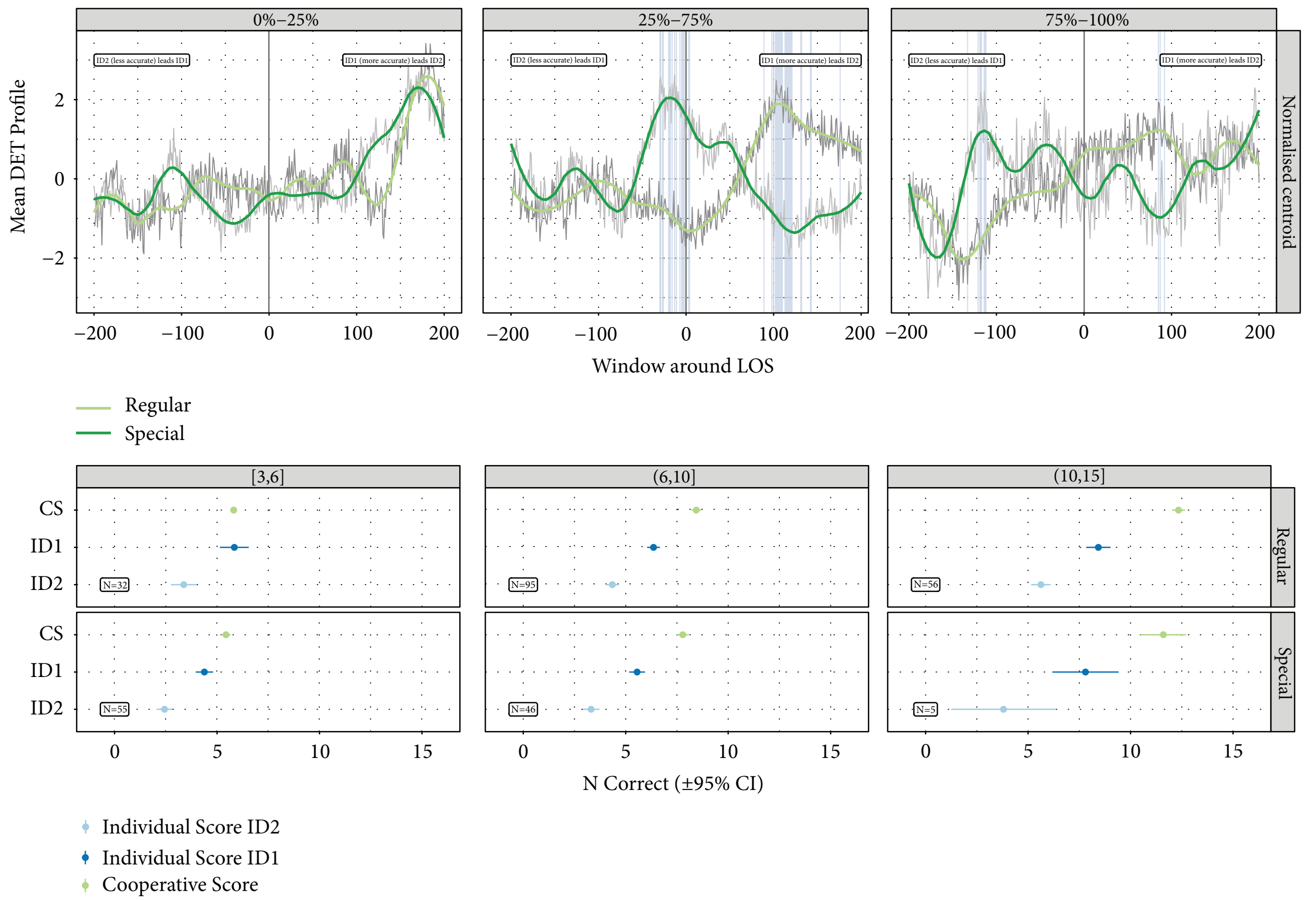

Figure 4: The upper panel (1st row) shows the leading-following centroid profiles for regular (light green) and special (dark green) primary education taken from a 40 second window (sampled at 5 Hz) around the line of synchronization (LOS) in the CRP. Columns 1-3 represent percentiles of the scores observed in the cooperative condition (lowest 25%, average 50%, and highest 25%, respectively). Prior to averaging, participants were sorted such that the highest scoring individuals on the premeasure in each dyad are on the left side of the LOS. Labels in the upper panel indicating which dyad member would be leading the interaction were a peak observed in that part of the profile. The blue vertical lines indicate at which points the regular and special education centroids differ significantly according to the permutation test (see text for details). The lower panels (2nd and 3rd rows) show the number of dyads and their performance in terms of correct puzzles in each group during cooperation (CS), and premeasure for the high-performing (ID1) and low-performing dyad member (ID2).

opposite was true for the best performing dyads, in which the low-performing dyad member was in the lead. The average group was somewhat in between these two, tending towards a more synchronized interaction.

4. Discussion

This study revealed that typically developing children exhibited relatively consistent coordination behavior when cooperating. The more skilled child (i.e., the one with the most correct puzzles on the individual measure) was the leader and the lesser skilled the follower. Note, however, the subtle difference between high- and low-performing dyads: in high-performing dyads, the less skilled child followed the "leader" more closely in time, which was visible in a decrease in delay across performance groups. Thus, the better performing dyads appear to have a more closely matched (in time) pattern of postural sway than low-performing dyads, suggesting that they are more optimally coordinated, which is consistent with findings by Abney et al. [16] and Vink et al. [17, 18].

A possible explanation for the success of typically developing children is that in the high-performing dyads the more cognitively skilled child may have been better at explaining or mediating how the task should be done. Fawcett and Garton [7] showed that it is not only about dyad composition, but that interaction also matters. The nature of the interaction is important considering the zone of proximal development [5]. By stepping into the less skilled child's zone of proximal development, the more skilled child may be able to increase the less skilled child's ability level. In addition, the more skilled child also has to be able to abandon the zone of proximal development of the less skilled child at some point, such that a state of disequilibrium in the interaction can emerge, a prerequisite for learning [45]. By stepping out of the zone of proximal development (i.e., stepping out of the state of equilibrium), the more skilled follower temporarily becomes the leader. This way, the less skilled child will experience a state of disequilibrium and may be invited to follow the leader in the hopes of regaining a state of equilibrium.

Another reason for the observed pattern in the typically developing dyads is that interactions will become more and more natural (i.e., more optimally coordinated), with members becoming more equal as skill increases. This is what Leonardi et al. [14] demonstrated in mother-infant vocal interactions. Following behavior by the mother decreased over time (i.e., as the level of competence increased), suggesting that coordination between mother and child increased (i.e., improved), with the interacting individuals becoming more similar or equal over time.

Children with a neurodevelopmental disorder, however, showed a less consistent pattern. In low-performing dyads, the more skilled child was in the lead, whereas in high-performing dyads the less skilled child entrained the more skilled child. In average-performing dyads, there was not a clear leader as indicated by their near-synchronized patterns of postural sway. Thus, typically developing children need a skilled leader, whereas children with a neurodevelopmental disorder in a high-performing dyad need a skilled follower.

As with typically developing children, we can also relate the results of the children with a neurodevelopmental disorder to Vygotsky's [5] zone of proximal development. Unlike typically developing dyads in which the more skilled child could mediate the solution (or process) to the less skilled child, in dyads of children with neurodevelopmental disorders the more skilled child may need to adjust to the needs of the less skilled child. Thus, in this latter group it appears to be important, at least for cognitive performance, that help or mediation is adjusted to the task as well as to children's needs. In other words, the zone of proximal development differs depending on whether one looks at the macro or micro level of behavior, and both are important.

The results of the present study also provide a more detailed picture of the coordination that takes place in the interaction between primary-school children. Abney et al. [16] and Vink et al. [17] showed that level of coordination was related to cooperative cognitive task performance. In addition, Vink et al. [18] showed that this pattern was the same for typically developing children and children with a neurodevelopmental disorder; that is, for dyads consisting of typically developing children as well as those consisting of children with a neurodevelopmental disorder, better task performance was accompanied by more coordinated behavior during the task, as was indicated by less deterministic and more chaotic patterns of interpersonal postural sway. The latter study, however, did not explain how a potential source of information can account for the observed difference in performance between these two groups. In the present study we showed that patterns of leading and following provide one such source of information. Although both groups showed similar leader-follower patterns in the lowest performing group, the patterns were opposite in the best performing dyads.

Our findings have important implications for educational and clinical practice. Teachers should be aware that cooperative learning is strongly influenced by dyad composition. Cognitive ability differences between dyad members not only determine group performance, but also affect who is leading and who is following. Dyad composition should be adapted to the goal of the task or the goal of one or both of the dyad members. In some cases, this may mean that an educational (or even social) goal of one dyad member conflicts with the goal of the other member. For example, a high-ability student with a neurodevelopmental disorder cooperating with a low-ability student may not profit as much from a collaborative task as his or her low-ability peer. Teachers may consider having children collaborate on one occasion with a child who is cognitively superior and on another with a child who is cognitively inferior.

Clinicians may want to learn from our study that children with a neurodevelopmental disorder should sometimes be put in a position in which they are allowed to take the lead. A quote from Gernsbacher [28, p. 145] concludes our message beautifully: "experience suggests that this is when parents—and professionals—need to enact *even more* reciprocity, need to share *even more* of the child's world, need to follow *even more* of the child's lead . . ."

Data Availability

Data files and analysis scripts used to produce the results presented here are available from the Open Science Framework (https://osf.io/cfgh7/).

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

Note that the samples described in this study have been used in earlier studies of Vink et al. [17, 18].

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Research Article

Self-Esteem as a Complex Dynamic System: Intrinsic and Extrinsic Microlevel Dynamics

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The variability of self-esteem is an important characteristic of self-esteem. However, little is known about the mechanisms that underlie it. The goal of the current study was to empirically explore these underlying mechanisms. It is commonly assumed that state self-esteem (the fleeting experience of the self) is a response to the immediate social context. Drawing from a complex dynamic systems perspective, the self-organizing self-esteem model asserts that this responsivity is not passive or stimulus-response like, but that the impact of the social context on state self-esteem is intimately connected to the intrinsic dynamics of self-esteem. The model suggests that intrinsic dynamics are the result of higher-order self-esteem attractors that can constrain state self-esteem variability. The current study tests this model, and more specifically, the prediction that state self-esteem variability is less influenced by changes in the immediate context if relatively *strong*, as opposed to weak, self-esteem attractors underlie intrinsic dynamics of self-esteem. To test this, parent-adolescent dyads ($N = 13$, $M_{age} = 13.6$) were filmed during seminaturalistic discussions. Observable components of adolescent state self-esteem were coded in real time, as well as real-time parental autonomy-support and relatedness. Kohonen's self-organizing maps were used to derive attractor-like patterns: repeated higher-order patterns of adolescents' self-esteem components. State space grids were used to assess how much adolescents' self-esteem attractors constrained their state self-esteem variability. We found varying levels of attractor strength in our sample. In accordance with our prediction, we found that state self-esteem was less sensitive to changes in parental support and relatedness for adolescents with stronger self-esteem attractors. Discussion revolves around the implications of our findings for the ontology of self-esteem.

1. Introduction

Individuals differ not only in their level of self-esteem but also in the extent to which their self-esteem is variable over time. The variability of *state self-esteem*, that is, the fleeting and in-the-moment experience of the self as positive or negative [1], has been found to be a critical factor associated with depression proneness [2], anger arousal, and hostility [3], as well as reactions to evaluative feedback [4] and self-concept clarity or integration [5, 6]. While the pervasive importance of state self-esteem variability is clear, it is as yet unclear from where state self-esteem variability, and individual differences therein, stems. There are broadly speaking two streams of research concerning state self-esteem, both pointing toward different explanations for state self-esteem variability. As we will describe below, there appears to be a theoretical and methodological chasm between these two streams of research. While each of them has contributed important understanding of self-esteem as a process, each neglects the other.

The common conceptualization of state self-esteem focuses on the role of *extrinsic* forces in bringing about variability of state self-esteem. This assumption is the cornerstone of the dominant conceptualization in the field, that is, the Sociometer Theory of Self-Esteem [7]. From this perspective, state self-esteem fluctuates around a resting baseline level [8] in response to “incoming information relevant to relational evaluation” ([9], p. 2), and it is seen as a “subjective index or marker of the degree to which the individual is being included versus excluded by other people” ([10], p. 519). As a result, “cues that connote high relational evaluation raise state self-esteem, whereas cues that connote low relational evaluation lower state self-esteem” ([9], p. 2). Within this line of research, researchers investigate whether state self-esteem increases and decreases after (usually *social*) cues, such as randomly assigned “bogus” approval or judgement from “peers” (Thomaes et al., 2010), imagined evaluations from peers (Leary et al., 1998), subliminaly presented words [11], real-life academic or peer problems (Reynolds and Repetti, 2008), social exclusion (during a study-exchange abroad; [12]), or global negative events [13]. In focusing on the reactivity of state self-esteem to the social context, the *intrinsic* forces acting upon state self-esteem have not received any attention within this line of research.

In contrast, emerging studies that utilize time series analyses focus solely on these intrinsic forces. These studies have shown that state self-esteem exhibits internally generated patterns of change (referred to as the *intrinsic dynamics* of a process; [14]) across the real-time time span (i.e., from moment to moment; [15, 16]) and across months [17, 18]. These studies found that self-esteem resembles a “fractal process,” characterized by long-range correlations and nonstationarity. This is an important finding, as fractal processes sharply contrast the kind of process one would expect from fluctuations around a stable baseline in response to temporally independent contextual cues (i.e., the common conceptualization). This was explicitly tested and shown in De Ruiter et al. [15]. These studies have thus brought attention to the necessity of investigating the intrinsic dynamics of state self-esteem. However, in focusing on the temporal structure of state self-esteem processes, they too have failed to examine the whole picture, where they have ignored (methodologically) the role of the extrinsic forces acting upon state self-esteem.

The aim of the current article is to demonstrate that state self-esteem variability emerges from the *interplay* between intrinsic and extrinsic forces. We suggest that this can best be understood from the perspective that self-esteem functions as a complex dynamic system, where state self-esteem variability is a microlevel process that emerges from a dynamic interplay between perturbations from the immediate context (i.e., extrinsic forces) and higher-order self-esteem attractors (i.e., intrinsic forces). By studying the interplay between intrinsic and extrinsic forces, we aim to extend the emerging research on the intrinsic dynamics of state self-esteem [15–18] and to provide support for the emerging conceptualization of state self-esteem as part of a complex dynamic system.

We explore the interplay between intrinsic and extrinsic forces based on the predictions stemming from the self-organizing self-esteem model [19]. This is a theoretical model of self-esteem as a complex dynamic systems, and it explains the precise nature of “intrinsic dynamics” in self-esteem, and how the interaction between intrinsic dynamics and contextual forces can bring about state self-esteem variability [19]. In empirically testing these predictions, we explore how pivotal properties of a complex dynamic system may be empirically studied in the field of self-esteem, including nested timescales of development, circular causality, bottom-up emergence of attractor-like patterns, and top-down constraint on lower-order variability. In this exploratory study of these processes, our aim is to generalize from data description to theory (of complex dynamic systems), rather than to a description of the population [20].

1.1. The Nature of the Intrinsic Dynamics of Self-Esteem. The self-organizing self-esteem model [19] asserts that state self-esteem is dynamically nested within a larger self-esteem system. State self-esteem experiences are the lower-order process within this system. State self-esteem experiences feed forward across time, eventually giving way to the emergence of a more stable higher-order pattern of self-esteem. These higher-order patterns of self-esteem then constrain the future variability of state self-esteem in such a way that the moment-to-moment development of state self-esteem is pulled in the direction of the existing higher-order self-esteem patterns and away from alternative kinds of self-esteem experiences. Together, these processes are part of a continuously bidirectional causal process (i.e., circular causality; Haken, 1997).

From a complex dynamic systems perspective, these higher-order patterns are formally referred to as *attractor states.* These are any highly absorbing states to which a system (which can be psychological system within a person, such as self-esteem, or a dyad, a family, or a society) frequently returns because only a small amount of energy is needed to maintain that pattern [21–23]. In this way, attractor states can be thought of as tendencies or habits.

Furthermore, more than one attractor state can emerge in a bottom-up fashion across time, where each one is a qualitatively different tendency or habit (i.e., multistability). Together, they form a larger *attractor landscape.* Each attractor within the landscape provides a separate set of top-down constraints on the system’s lower-order processes.

The process of circular causality is often illustrated with an *epigenetic landscape*, consisting of valleys and a moving ball (see Figure 1). Each valley represents a different attractor state that pulls lower-order development (i.e., the movements of the ball) in a different direction.

The landscape illustrates that the lower-order process (i.e., the ball) is more likely to roll into the wider valleys, as more conditions lead to this point. Once in a valley, the deeper the valley the more energy that is needed to remove the ball from the valley. Wider and deeper valleys thus represent stronger attractor states that have a larger “pull” on the moment-to-moment variability of the lower-order process. Stronger attractor states are those that have become more entrenched across time [24, 25].

In the current article, we focus on two properties of the attractor landscape in our illustration of self-esteem as a complex dynamic system. First, the notion that a system is characterized by an attractor landscape highlights that individuals may have more than one self-esteem tendency. This is in contrast with the common idea that individuals have

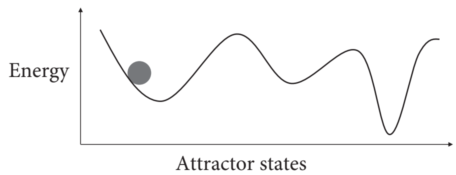

Figure 1: An attractor landscape, consisting of coexisting attractor states. Each attractor state is represented by a valley that provides a unique set of constraints on the movements of the ball. These movements represent the variability of lower-order components of the system. From De Ruiter et al. [19].

one baseline level of self-esteem [8, 10]. For example, if an individual systematically fluctuates between experiencing very high and very low state self-esteem, the iterative experience of these two qualities of state self-esteem will eventually give way to two relatively stable tendencies of self-esteem (i.e., very low and very high). Within any given situation, this specific individual will thus be drawn toward two competing tendencies of self-esteem (i.e., two attractors).

The second property of the attractor landscape that we will focus on is the constraining effect that an individual's self-esteem attractor landscape has on lower-order processes of self-esteem. Higher-order self-esteem attractors limit the degrees of freedom of state self-esteem variability. In this way, an individual's state self-esteem process (and specifically, the valence of this process, where the individual can experience himself as relatively negative or positive) is "drawn to" these self-esteem tendencies in real time. If the individual has a deeply entrenched attractor for high self-esteem and a weak attractor for low self-esteem, his state self-esteem process will be more strongly pulled toward positive valence.

The constraining effect that self-esteem attractors have on the valence of moment-to-moment self-experiences has been demonstrated empirically in a study of real-time self-evaluative narratives [26]. In this study, individuals' self-narratives were recorded, and afterwards the individuals mapped the moment-to-moment changes in valence that occurred during their self-narratives. The study showed that the flow of individuals' self-narratives was structured by their person-specific landscape of self-evaluation attractors. Moreover, there were clear individual differences in the quality of individuals' attractors (i.e., positive or negative) and in the constraint that these attractors had, predicted by individual differences in self-concept clarity. The study therefore showed that temporal variability in self-narratives is constrained by an individual's self-evaluation attractor landscape.

1.2. The Interplay between Intrinsic Dynamics and Contextual Forces. A key aspect of the self-organizing self-esteem model, and focus in this article, is the notion that self-esteem attractors that are relatively entrenched will inflict greater constraint on the moment-to-moment variability of state self-esteem. The SOSE model predicts that, as a consequence of this, it will be more difficult for the immediate social context to perturb the flow of state self-esteem from its current position given more entrenched (i.e., stronger) self-esteem attractors. There is therefore a constant interplay between these two forces acting upon state self-esteem. As a result, we suggest that the "reactivity" of state self-esteem to social cues must be seen in the context of the strength of self-esteem attractors. This is portrayed in Figure 2.

For individuals with relatively weak self-esteem attractor states, these attractor states will provide lower constraint on the moment-to-moment variability of state self-esteem. As a result, it will be relatively easy for the immediate social context to perturb the flow of state self-esteem and to move it from its current position, resulting in more reactivity [19].

While studies frequently find that state self-esteem is particularly responsive to the social context ([12]; Leary et al., 1998; Reynolds and Repetti, 2008; Thomaes et al., 2010), the SOSE model extends this by predicting that individual differences in the degree of attractor states' entrenchment will have direct consequences for how *easily* the social context will trigger changes in state self-esteem.

In linking properties of self-esteem attractor landscapes to individual' vulnerability to changes in the social context, this prediction describes the mechanism potentially underlying previous findings involving self-esteem and low *self-concept clarity* (i.e., lack of a clear—integrated, consistent, or certain—sense of self). Low self-concept clarity has been found to correspond with higher levels of temporal variability of self-esteem (Nezlek and Plesko, 2001; [16]) and more unstable and abrupt shifts in self-esteem [26]. As Wong et al. [26] have suggested, this indicates that low self-concept clarity may be the signal of "weak attractors …, such that the self-system cannot settle on specific states of self-esteem that provide stable frames of reference for thought, feeling, and action" ([26], p. 168). Furthermore, lower self-concept clarity is associated with more temporal instability of self-esteem [27]. From our framework, this can be explained by weaker self-esteem attractors, as weak attractors provide a low level of constraint on state self-esteem processes, leaving them more vulnerable to daily events. This would provide an explanation for the more general finding that self-feelings of individuals with unstable (as opposed to stable) self-esteem are more impacted by daily negative events [28–30].

1.3. The Current Study: Empirically Testing the Interplay between Intrinsic Dynamics and Contextual Forces. Based on the abovementioned conceptualization and predictions, we hypothesize that there will be a negative within-individual relationship between the level of self-esteem attractor constraint and the influence that the social context will have on state self-esteem: for individuals whose self-esteem attractors have *more* constraint on their state self-esteem variability (i.e., stronger self-esteem attractors), state self-esteem will be *less* affected by contextual changes. In contrast, in individuals whose self-esteem attractors exhibit *less* constraint on their state self-esteem variability (i.e., weaker self-esteem attractors), state self-esteem variability will be *more* affected by contextual changes. This study focuses specifically on self-esteem processes of adolescents, as adolescence is a significant period for self-esteem development

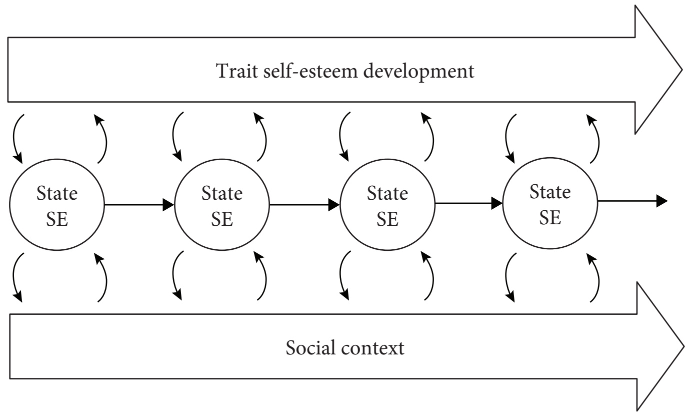

Figure 2: Two forces acting upon state self-esteem (SE): self-esteem attractors have a degree of constraint on state self-esteem variability, and the immediate social context can perturb state self-esteem variability (adapted from [19]).

[31]. In the following section, we outline the empirical approach that is taken in order to test this hypothesis.

In accordance with Gelman's (2017) recommendations, we focused our data-collection efforts on the quality (i.e., relevance and accuracy) of our measures, design, and analyses in relation to our test of specific theoretical predictions, rather than, for example, larger sample sizes to infer population tendencies. Given our goal to explore real-time processes and to use these descriptions to support a theoretical idea (rather than a generalization to the population), the intensive real-time data collected and methods utilized were highly suited to our specific research aim.

1.3.1. State Self-Esteem: An Observational Approach. Currently, studies that use high-frequency measures of state self-esteem across time have intervals of half a day or a day between measures (e.g., [5, 12]). Such studies use the common self-report method to measure state self-esteem, therefore operationalizing self-esteem as the primarily *cognitive* experience of one's self-concept as positive or negative.

For our purpose of studying *real-time* variability of state self-esteem, it is intuitively no longer valid to assume that individuals actively reflect on the valence of their self-worth from moment to moment. Instead, the nature of self-esteem at this timescale is more social and emotional and should be measured as such [32]. Moreover, the very act of reporting on the momentary experience of one's self would disrupt the organic and continuous process of state self-esteem experiences and thus the intrinsic dynamics that we are studying. To remedy this, we must therefore adopt a novel methodological approach to the measurement of state self-esteem processes.

Previous researchers have suggested that using an observational method provides a valid measure of self-esteem, especially in the case of adolescents (who may be prone to self-enhancement tendencies; [32–34]). Furthermore, this approach provides a fine-grained measure for the moment-to-moment dynamics of self-esteem without interrupting those dynamics as they unfold over time. In the current study we, we therefore take an observational approach to adolescents' real-time self-esteem. We investigated adolescents' self-esteem in the context of dyadic interaction with parents. Parents are a key significant other for adolescents' self-esteem [35, 36], thus providing a practical and theoretically valid way to elicit relevant self-esteem processes [37].

We measured two underlying components of adolescents' global self-esteem that can be observed during interactions with their parents. Self-esteem is thought to have two dimensions, self-liking and self-competence. *Self-liking* refers to the experience of oneself as a good or bad social object according to internalized criteria of worth [38]. This dimension can be measured by means of real-time expressions of self-relevant emotions (i.e., positive to negative self-affect), such as pride or embarrassment [32, 33]. The second dimension, *self-competence*, refers to the experience of oneself as a causal agent with efficacy [38]. In the context of parent-adolescent interactions, this dimension can be measured by means of real-time autonomy-exhibiting behavior (i.e., autonomy to heteronomy), such as communicating an opinion or asserting one's self [34, 39, 40].

State self-esteem as a *process* was therefore operationalized as the moment-to-moment changes in the valence of expressed behavioral and emotional indicators of adolescents' self-esteem. As such, state self-esteem can be seen as a lower-order self-esteem construct that changes in quality (i.e., varying weight of autonomy versus self-affect) and intensity from moment to moment. This corresponds with the notion of self-esteem as "a positive or negative response to oneself that can take a variety of forms" ([41], p. 35). Concretely, the moment-to-moment changes in valence form a time series for each individual. We captured the time-varying trends of these time series using the Loess smoothing technique [42].

The use of observable expressions of self-affect and autonomy as underlying components of state self-esteem was first demonstrated in De Ruiter et al. [15], where the temporal variability of adolescents' state self-esteem was examined. The study showed that, firstly, this temporal variability demonstrated intrinsic dynamics that resembled a fractal process, and secondly, that this variability was significantly different from the kind of variability that would be generated from fluctuations around a stable baseline. As such, this previous study—like others that have studied the temporal dynamics of self-esteem [16, 17, 26, 43]—did not test the role of the immediate context; nor did it examine differences between individuals' intrinsic dynamics. The current study builds upon those earlier findings by testing the simultaneous interplay between intrinsic dynamics of self-esteem and the extrinsic dynamics in the social context and by examining differences between individuals.

1.3.2. Intrinsic Microlevel Dynamics: State Self-Esteem Variability and Recurring Self-Esteem Patterns. Based on the SOSE model, state self-esteem processes (i.e., as lower-order processes of self-esteem) alone do not create *intrinsic dynamics* of self-esteem. Instead, intrinsic dynamics are expected to arise due to the constraint that self-esteem attractors have on state self-esteem processes.

"Self-esteem attractors" were operationalized as qualitatively different patterns of adolescents' lower-order self-esteem components that self-organized—and repeatedly recurred—across the interaction. We captured self-esteem attractors with Kohonen's self-organizing maps [44]. This is a clustering technique that finds structure in multivariate time-serial data that have "self-organized" across the time series. It is widely used outside of psychology, but has been recently introduced to psychology for the use of studying intraindividual variability of multivariate time-serial data [45]. The technique thus finds (recurring) structure that has emerged from iterations of the lower-order multivariate data and can be expressed as a higher-order construct, similar to attractors. As such, we do not define attractors by mathematical means, but by a qualitative theory of attractor mechanisms (i.e., self-organization from lower-order components into patterns, and repetition of said patterns across time). The qualitative attractors that we define and measure in the current study are in this sense attractor-*like*, in comparison to the definition of mathematical attractors.

Next, the "self-esteem attractor constraint" that underlies intrinsic dynamics of self-esteem was operationalized as the extent to which real-time transitions to and from specific self-esteem attractors coincided with specific changes in state self-esteem variability. This was done using state space grids [46, 47]. This is an application of the standard "state space" concept of dynamic systems to categorical dimensions, therefore dividing the state space into a grid. The grid depicts a two-dimensional (categorical) state space by portraying the dynamics between two synchronized streams of data. While this is often used to study the dynamics between two individuals, we have used it to study the dynamics between one lower-order stream of events (i.e., state self-esteem) and one high-order stream of events (i.e., transitions between self-esteem attractors). This operationalization reflects the landscape notion of self-esteem attractors, where each valley represents a different attractor state that pulls lower-order processes toward that point and where deeper valleys provide more constraint on lower-order variability than shallow valleys do. From this conceptualization, while a *strong* self-esteem attractor state is expressed, we would expect to observe limited state self-esteem variability. Moreover, we would expect each attractor to provide its own set of constraints on lower-order variability, such that the expression of that attractor state corresponds with a certain range of state self-esteem valence (e.g., high self-esteem, but not low self-esteem). Thus, the repeated expression of that specific self-esteem attractor would correspond with state self-esteem returning to the same approximate levels as the previous time that attractor was active.

In summation, self-esteem attractor constraint was identified by each attractor's ability to limit the degrees of freedom of state self-esteem while it is expressed *and* by the attractors' ability to pull state self-esteem to the same approximate level each time it is active. As such, our definition of attractor constraint is based on qualitative theory of these mechanisms, just like our definition of attractors themselves. Our operationalization of attractor constraint is therefore of constraint-*like* behavior.

1.3.3. Extrinsic Microlevel Dynamics: Parental Expressions of Emotions and Behavior. As research shows that self-esteem is particularly influenced by significant others and their behavior (e.g., [48, 49]; Fogel, 1993), studying self-esteem processes in the context of parent-child interactions provides a theoretically solid foundation for assessing the impact of perturbations (i.e., extrinsic forces) on adolescents' self-esteem.

Perturbations are changes (such as changes in context, goals, or demands) that result in a shift in a state or pattern. The nature of a perturbation depends on the time scale that is considered [50]. For example, a move from primary school to secondary school can be considered a perturbation that occurs at a larger time scale, while a shift in the emotional intensity of a conversation can be considered a perturbation that occurs at a smaller time scale. Since we will be examining self-esteem changes that occur across real time, we are interested in these latter forms of moment-to-moment perturbations.

Moment-to-moment changes in parents' expressed emotions and autonomy support were treated as potential real-time perturbations (i.e., in the here and now). The reason for focusing specifically on parents' expressed emotions and autonomy support is based on the fact that adolescents are faced with the critical developmental task of achieving autonomy within the parent-child relationship while maintaining connectedness in the relationship [48, 51–53]. The extent to which this critical task is met is central in determining adolescents' sense of self [40]. As such, characteristics of the parent-child relationship that specifically support the achievement of this critical task are often associated with adolescents' self-esteem. This includes parental *expressions of connectedness* (i.e., closeness and warmth toward the child; [54])—facilitating the maintenance of connectedness in the relationship—and *autonomy support* (i.e., supporting or challenging the child's independence of thought and behavior; [55–57])—facilitating the achievement of autonomy within the relationship. These specific aspects of the parent-child interaction were therefore central in our study of the perturbations acting upon adolescents' state self-esteem.

We will refer to moment-to-moment changes of parental expressions of connectedness and support as changes in

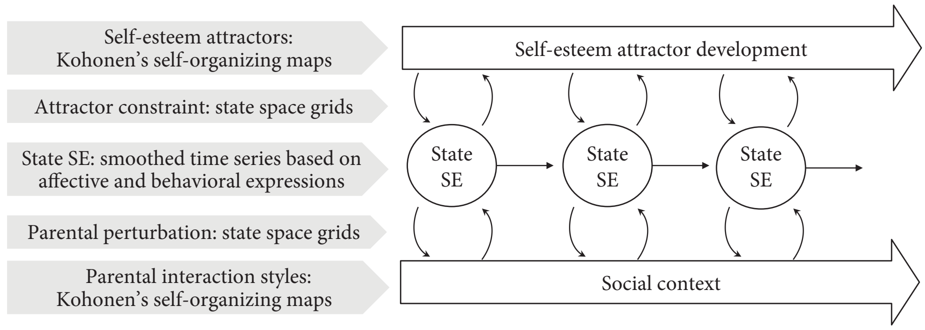

Figure 3: Overview of the methods used to capture the various processes involved in the interplay between self-esteem attractors and the immediate social context acting upon state self-esteem (SE).

"parental interaction styles." We will map the real-time dynamics between these interaction styles and the adolescent's state self-esteem, and when a real-time change in parental interaction styles corresponds temporally with a change in the valence of the adolescent's state self-esteem, this will be referred to as a "parental perturbation."

We captured real-time parental interaction styles using Kohonen's self-organizing maps [44], and we mapped the moment-to-moment dynamics between these interaction styles and the adolescents' state self-esteem with state space grids [46, 47].

In summation, in the current study we aimed to capture all processes involved in the continuous interplay between intrinsic dynamics and extrinsic forces acting upon state self-esteem (i.e., the processes outlined in Figure 3). We attempted to capture these processes with a number of different techniques, outlined in Figure 3 below. These techniques will be explained in more detail in Results.

2. Methods

2.1. Participants. Participants were thirteen adolescents (10 girls, 3 boys) and their parents (12 females, 1 male). The mean adolescent age was 13.6 (ranging from 12 to 15). The majority of the dyads were Dutch-speaking, with the exception of two English-speaking dyads (one American-Dutch dyad and one British dyad). Participation was voluntary, and children were rewarded after the interaction task was completed with a 5 Euro gift voucher. Parents gave informed consent for their children.

2.2. Procedure. Each dyad was video-recorded in their own home during a discussion. Each discussion was structured around three topics in which the aim of the discussion was to come to a mutual decision. The first discussion topic was a positive discussion topic (e.g., If you could have one super power, which would you have?). The second was a conflict topic relevant to each specific dyad at that moment, where the dyad was instructed to try to come up with a solution to their problem. The last discussion topic was a new positive topic comparable to the first (i.e., A-B-A design, Granic et al., 2007; [58]). In assigning both neutral and conflict topics, a range of self-evaluative emotions and behavior are potentially elicited [24, 58]. Dyads were told that they could move on to the next topic when they felt they were finished, keeping in mind that they should take about five minutes for each topic. The dyads were reassured that there was no "right" or "wrong" thing to say or do and that the researchers are interested in their natural responses to each other. The researcher then left the dyads alone in a room of their choice for the duration of the filming. Afterwards, the observational videos were coded for their emotional and behavioral content.

2.2.1. Coding Procedure. Based on the video-recorded interactions, we coded adolescents' affective and behavioral expressions of state self-esteem, and affective and behavioral components of parents' broader interaction styles (see Measures, below). The raw data for the current study were previously used in De Ruiter et al. (2016)), where only the adolescents' data were used.

Coding of emotions was largely based on the Specific Affect (SPAFF) coding system [59], where physical cues are used to indicate different emotions. Adaptations were made in order to distinguish between self-directed affect and other-directed affect and were data-driven (in accordance with the Grounded Theory approach; [60]). Coding of autonomous behavior was largely based on Savin-Williams and Jaquish's behavior checklist for adolescents' self-esteem [34]. This checklist was further expanded upon using on Noom et al.'s [61] framework of emotional, functional, and cognitive autonomy during adolescence. Coding of parental affect and behavior was based on theory regarding parental autonomy support and connectedness [48, 62].

Coding was event-based (using the program The Observer XT 10.5), such that a code was given for each relevant verbal/nonverbal expression across the interaction. Observers were extensively trained until at least 75% agreement was reached before coding commenced. Average between-observer agreement for coders who independently coded 10% of the event-based data was sufficient, with Cohen's kappa = 0.69 for autonomy-related behavior for parent and adolescent, 0.82 for self-affect, and 0.74 for connectedness.

2.3. Observational Measures. Observational measures were obtained for both adolescents and the parents. For both, emotions were ordered from most aversive (e.g., shame) to most positive (e.g., pride), similar to the ordering of emotions done in the studies by Hollenstein et al. [58, 63]. Behaviors were ordered from most autonomous (e.g., confronting the other) to the most heteronomous (i.e., submitting to the other; [61]).

2.3.1. Adolescent Measures. Self-affect is self-directed affect. This measure was used as an indicator for adolescents' state self-esteem. Both positive self-affect and negative self-affect were scored. Positive self-affect was scored on a scale of 0 to 3, which includes 0 = neutral, 1 = self-interest (e.g., adolescent speaks enthusiastically about an idea she/he has), 2 = humor (e.g., adolescent laughs in self-assured manner while speaking/behaving), and 3 = pride (e.g., adolescent compliments him-/herself). Negative self-affect was scored on a scale of 0 to −3, which includes 0 = neutral, −1 = embarrassment (e.g., adolescent speaks with eyes cast down), −2 = anxiety (e.g., adolescent fidgets and avoids eye contact while opposing parent), and −3 = shame (e.g., adolescent speaks in sad and serious tone during self-invalidation). Positive and negative self-affect could be simultaneously scored if verbal and nonverbal expressions conflicted. Note that *self-affect* only includes "self-conscious" emotions, which are socially situated emotions pertaining to the self (Tangney and Fischer, 1995). These are in contrast with emotions that are not self-conscious, such as affection or anger, which reflect appraisals of the context and concerns in an immediate relationship (Frijda, 2001).

Autonomous actions was used as an indicator for adolescents' state self-esteem. It was scored on an ordinal scale of −2 to 3 (the scale is not symmetrical as there were more categories for autonomous behavior compared to heteronomous behavior), where −2 = submission (e.g., adolescent changed opinion in accordance with what parent thinks without offering counter arguments), −1 = attitudinal heteronomy (e.g., adolescent expressed not knowing the answer to a question that did not require specific knowledge), 0 = neutral, 1 = attitudinal autonomy (e.g., adolescent contributed an idea), 2 = agency (e.g., adolescent initiated a change in discussion topic), and 3 = self-assertion/confrontation (e.g., adolescent rejected accusation made by the parent).

Connectedness is other-directed affect, which was scored for the adolescent during or directly following the parents' utterances or actions. This was coded to determine self-experiential incoherence, a conditional measure necessary to ensure that *true* state self-esteem is captured (see Self-Experiential Incoherence, below). Both positive connectedness and negative connectedness were scored. Positive connectedness was scored on a scale of 0 to 3, which includes 0 = neutral, 1 = other-interest (e.g., adolescent smiled while parent spoke), 2 = other-joy (e.g., adolescent laughed while/after parent spoke/acted), and 3 = affection (e.g., adolescent hugged parent). Negative connectedness was scored on a scale of 0 to −3, where 0 = neutral, −1 = other-disinterest (e.g., adolescent looked away and turned body away while parent spoke), −2 = other-frustration (e.g., adolescent responded to parent with whining tone), and −3 = contempt (e.g., adolescent expressed hurtful comment in sarcastic tone). Positive and negative connectedness was simultaneously scored if verbal and nonverbal expressions conflicted. An example of this is if the adolescent verbally expressed connectedness by laughing when the parent told a joke, while expressing a hurtful comment toward the parent in a sarcastic tone.

2.3.2. Parental Interaction Measures. Parental connectedness is other-directed affect, which was scored for the parent during or directly following the adolescent's utterances or actions. The scoring for parental connectedness is the same as for the adolescent (see above).

Parent self-affect is self-directed affect. Both positive self-affect and negative self-affect were scored. The scoring for parental self-affect is the same as for the adolescent (see above).

Autonomy management was scored on an ordinal scale of −2 to 3, where −2 = confrontation/pressure to submit (e.g., parent criticized the child's idea and suggested own idea as alternative), −1 = parent controlled the child (e.g., correcting the child), 0 = neutral (e.g., parent neither supported nor challenged the child's autonomy), 1 = encouragement (e.g., parent encouraged the child to continue explaining his/her idea), 2 = small validation (e.g., parent provided minimal encouragement by nodding while the child spoke), and 3 = large validation (e.g., parent complimented the child).

2.3.3. Self-Experiential Incoherence. Self-experiential incoherence is a dummy variable that was scored for the adolescents and parents after coding (of the abovementioned measures) took place. Based on Kernis' [29] suggestions, this measure was scored if an individual's simultaneous emotional and behavioral codes suggest disingenuous behavior. This is the case in the following scenarios: positive self-affect *and* negative self-affect were coded, positive connectedness *and* negative connectedness were coded, or negative autonomy *and* positive self-affect were coded [29]. These instances all suggest that the individual is "misrepresenting their feelings" by not divulging negative behaviors or self-aspects ([29], p. 13). Kernis [29] states that, while the individual may be expressing positive self-aspects, such scenarios do not indicate *true* self-esteem [39]. As such, while positive self-affect and autonomy can be seen as indicators of positive state self-esteem, it is vital that these indicators are not considered in isolation from each other. In scenarios of self-experiential incoherence, indicators of positive self-esteem (i.e., positive autonomy or positive self-affect) would not indicate *true* positive self-esteem if considered in isolation.

In this study, we wanted to ensure that we were capturing processes of true self-esteem. Therefore, self-experiential incoherence was measured and used in our calculation (as a conditional variable) of state self-esteem (see Variability of State Self-Esteem, below). Self-experiential incoherence was also included for the parent as information regarding the extent to which the parent was behaving genuinely or ingenuously toward the adolescent during the interaction.

2.4. Analysis Plan. The general aim of the analyses was to attempt to map the various mechanisms involved in a complex dynamic systems model of self-esteem and to test whether they related to each other in ways that we would expect given this conceptualization. We focused on attractor-like constraint that higher-order recurring patterns of self-esteem have on lower-order SSE variability, as well as the perturbing effects of the immediate social context on SSE variability (Figure 2). For this aim, only the *temporal order* of variability (of state self-esteem) and of transitions (of higher-order recurring patterns) was considered relevant. The focus was therefore on the structure of the time series, not on the absolute levels or content of self-esteem or the parental measures themselves (This is the first foray into testing the Self-Organizing Self-Esteem model and thus the first attempt to test simultaneous processes of attractor constraint and perturbations in the context of self-esteem. Therefore, the data only allow for estimations of these complex processes and for suggestions that formal attractors exist. For the purpose of efficiency, we will use "self-esteem attractor" to refer to attractor-like patterns and "attractor constraint" to refer to constraint-like behavior.).

The analysis consisted of a number of steps, where each step involves a different method. Here we provide an overview of each step in the analysis and the respective analytical method. The analytical methods themselves will be further elaborated on in the relevant results section:

(1) Capturing moment-to-moment processes of

  (a) Variability of state self-esteem (SSE)

  (b) Transitions between "self-esteem attractors" using Kohonen's self-organizing maps

  (c) Transitions between "parental interaction styles" using Kohonen's self-organizing maps

(2) Using state space grids to map the temporal correspondence between the variability of SSE (from step 1) and

  (a) Higher-order patterns of "self-esteem attractors" (from step 1b) to determine the level of "attractor constraint" on state self-esteem variability

  (b) Higher-order patterns of "parental interaction styles" (from step 1c) to determine the level of "parental perturbations" on state self-esteem variability

(3) Comparing the within-individual level of "attractor constraint" (from step 2a) with the level of "parental perturbations" (from step 2b) for each individual using a Monte Carlo bootstrapping method

3. Results

3.1. Part 1: Capturing Moment-to-Moment Processes

3.1.1. Variability of State Self-Esteem (Step 1a). State self-esteem (SSE) time series were calculated based on the sum of the behavioral (i.e., autonomy) and affective (i.e., self-affect) indicators of the adolescent's self-esteem *for each moment* in the interaction (see the section *Adolescent Measures*, which describes the various observational measures). To ensure that *true self-esteem* was captured [29, 64], the presence of these indicators was not considered in isolation from each other. A positive affective or behavioral indicator was only deemed as a true indicator of positive self-esteem given the absence of a self-experiential incoherence code (self-experiential incoherence = 0). The calculation for SSE_t was conducted in Microsoft Excel (Version 2010) and is described by

$$\mathrm{SSE}_t = (\mathrm{SA}_t + \mathrm{AU}_t)\,; \quad \text{if } (\mathrm{SEI}_t = 0)\,; \quad \text{otherwise}, 0, \qquad (1)$$

where SA_t is self-affect, AU_t is autonomy, and SEI_t is self-experiential incoherence at t_x.

The state self-esteem time series and the lower-order input time series (i.e., self-affect and autonomy) were smoothed for the subsequent analyses. This was necessary to smooth out the "neutral" moments (similar to missing data points) in the interaction that were coded when the individual did not do anything (because they were, e.g., waiting for the discussion partner to respond). During the coding process, a zero was coded for these neutral moments. When treated as a time series, this resulted in artificially large fluctuations (e.g., t_1 = child expresses frustration (connectedness = −2), t_2 = child is silent while listening (connectedness = 0), and t_3 = child continues to express frustration (connectedness = −2)). The coding of zeroes during moments in which an individual was silent therefore resulted in noisy time series. To remedy this, we smoothed the data to correct for this artifact of the coding process.

Smoothing was done with a LOESS smoothing technique [42], which is the most common method used to smooth noisy time series. Loess smooths by conducting a local regression around each score of the time series. We did this in a window of 20% of the data. The window is sequentially moved across the scores in the time series (i.e., a *moving window*). The values within the moving window are weighted on the score at that second. The smoothing process thus compresses the scale of the measures, while following the general trend of the data and thus protecting the temporal structure [65]. Given that only the temporal structure of changes in variables was important for our study (not the absolute level of variables), the change in scale did not jeopardize the validity of the current analyses. An example of the smoothed lower-order time series (self-affect and autonomy) and the state self-esteem time series is shown in Figure 4. The length of the time series across our sample was $M = 847.3$ seconds (SD = 192.2).

3.1.2. Transitions between Higher-Order Patterns (Steps 1b and 1c). We captured higher-order patterns of recurring self-esteem attractors and parental interaction styles using Kohonen's self-organizing maps (SOM; [44]).

(1) Kohonen's Self-Organizing Maps. Kohonen's self-organizing maps is a data-mining technique that maps the spatial and temporal emergence of structure in time-serial

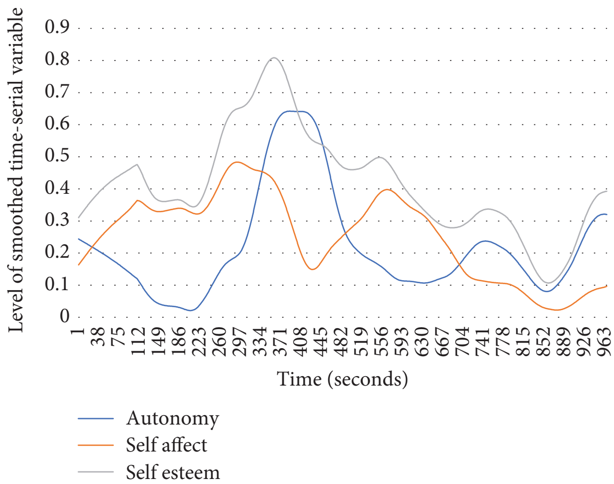

Figure 4: Example of an individual's lower-order time-serial variables (self-affect and autonomy) and their state self-esteem time series.

data. The SOM analysis was done in the program Tanagra 1.4.41 [66], which is free data-mining software.

Using unsupervised learning algorithms, SOM derives a map of the data for each individual. A map is a small set of qualitatively different "clusters" that show the underlying structure of the individual's input data. An "unsupervised learning algorithm" means that the clusters are discovered in a recursive process by means of the input data and hence not specified by the researcher beforehand. The SOM learning process works by recursively comparing pairs of vectors: an empirical vector that represents the input data and a model vector (from the emerging map). The model vector is continuously calculated and updated based on the value of the empirical vector and its position on the time series. If the vectors differ, the model vector is altered slightly so that dissimilarity is reduced. This is repeated multiple times, where at each step an empirical vector is presented to a new model vector, until the map fully represents the structure of the empirical data. Through this process, the accuracy of the map continuously improves with each iteration as it "learns" to represent the structure of the data. When the learning process is finished, the final map optimally represents the organization of the data across time [44].

The resulting map reveals the organization of each individual's data as new higher-order output, represented by the moment-to-moment transitions between the recurring clusters. Because we used this technique to capture within-individual structure, each individual has a unique map (i.e., set of clusters). The clusters differ with regard to their quality and their temporal patterns of recurrence. Regarding the quality, each cluster is defined by the variables (i.e., input data) that are most salient in that specific cluster and by the relationships between the variables within the cluster (see the Appendix for an example of the quality of clusters for two individuals). This means that each variable can contribute to multiple clusters within an individual's map, such that each cluster represents a different relationship between the same variables. Thus, rather than collapsing the "time" component of the data and determining the statistical similarity between the various variables, the SOM determines the dynamic correspondence between time-serial variables [67].

Regarding the temporal patterns of each cluster, the SOM keeps track of the time point that each data point falls into the various clusters [68]. Therefore, the resulting clusters keep the "topological structure" (i.e., the relationship between data points *over time*) intact. Because of this, an individual's emergent map includes information regarding when, and for how long, each cluster is expressed across the time series. This information is in the form of a new (higher-order) time series, generated for each individual. The time series show the moment-to-moment transitions between the individual's clusters across the time span of their time series. This is the crucial information for the current study, as we are interested in the temporal pattern of these higher-order structures, rather than the idiosyncratic quality of the structures. This temporal pattern is what was used to determine the temporal correspondence with state self-esteem variability in step 2 of the analysis. The temporal recurrence of clusters is illustrated in the following section (in Figure 5).

This technique has been demonstrated and described in De Ruiter et al. [45] as a useful method for studying real-time development of multivariate data at the intraindividual level. For more specifics regarding the SOM algorithm and the specific learning rules, see Kohonen [44].

(2) Kohonen's Self-Organizing Maps in the Current Study. For the current study, we used the SOM technique to obtain a higher-order map (i.e., a collection of person-specific clusters) of each adolescent's self-affect, autonomy, and self-experiential incoherence. These idiosyncratic maps were our operationalization of the adolescents' "self-esteem attractors," as they revealed qualitatively different patterns of adolescents' lower-order self-esteem components that self-organized—and repeatedly recurred—across the interaction (for our rationale, see The Current Study: Empirically Testing the Interplay Between Intrinsic Dynamics and Contextual Forces). When conducting SOM, the researcher must determine how many clusters will make up the map. Based on Wong et al.'s [26] finding that most participants revealed two attractors of self-evaluation during self-narratives, we captured two self-esteem attractors (i.e., a map consisting of two clusters) for each adolescent. For ease of interpretation, and because the content of the attractors is not relevant here, we call these clusters "self-esteem attractor 1" and "self-esteem attractor 2" for each adolescent.

Recall that the SOM analysis maintains the temporal structure of the emergent clusters for each individual and portrays this temporal structure as a new time series. These time series include the timing and duration of transitions between the two clusters. To illustrate, Figure 5 shows self-esteem attractor time series for two different individuals (A and B). As only the duration and transitions between each individual's clusters are relevant for this study, we have not included the SOM output that refers to the quality of the

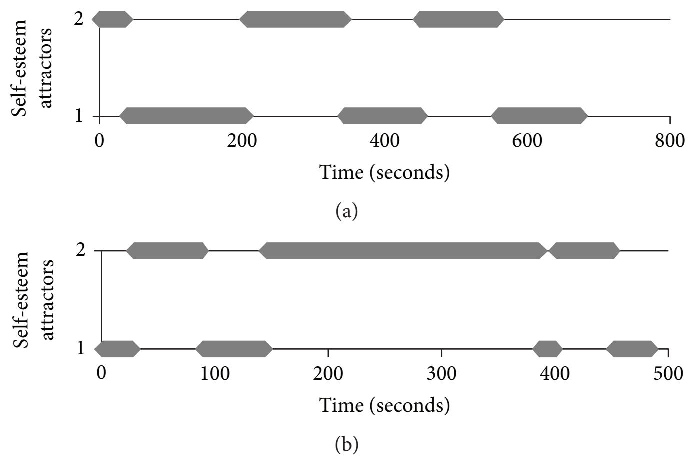

Figure 5: Empirical examples of self-esteem attractor time series across the dyadic interaction for two participants (a and b). The grey bars indicate the duration of time (i.e., seconds) that the self-esteem attractors (1 and 2) are expressed.

clusters (see the Appendix for the content output corresponding with participants A and B from Figure 5).

We also used the SOM technique to obtain a higher-order map of each parents' parental connectedness, autonomy management, and parental self-experiential incoherence. These maps were our operationalization of "parental interaction styles," as they revealed qualitatively different patterns of parental expressions of affect and behavior toward the child during the interaction. In order to make within-individual comparisons between parental interaction style transitions and transitions between self-esteem attractors, we also captured two parental interaction styles (i.e., a map consisting of two clusters) for each parent. We call these two clusters parental interaction style 1 and parental interaction style 2 for each parent.

3.2. Part 2: Mapping the Temporal Correspondence between SSE Variability and Higher-Order Patterns. In this step, we measured the extent to which transitions to and from individual's clusters (self-esteem attractors 1 and 2; parental interaction styles 1 and 2) coincided with specific changes in state self-esteem variability.

For self-esteem attractors, temporal correspondence with SSE variability refers to the level of "self-esteem attractor constraint." If the expression of a given self-esteem attractor (e.g., self-esteem attractor 1) predominantly corresponded with a certain level of SSE across the interaction (e.g., medium to high), and if the SSE level remained relatively stable (i.e., medium to high) while that self-esteem attractor (i.e., self-esteem attractor 1) was expressed, we refer to this adolescent's self-esteem attractors as having a high level of constraint on state self-esteem variability. This corresponds with the conceptualization that strong attractors have a strong pull on lower-order processes and that lower-order variability of lower-order processes is limited while the attractor is expressed (see The Current Study: Empirically Testing the Interplay Between Intrinsic Dynamics and Contextual Forces).

For parental interaction styles, temporal correspondence with SSE variability refers to the level of "parental

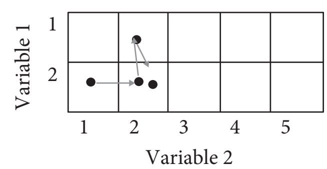

Figure 6: Illustration of four events of a hypothetical variable 1 (y) and variable 2 (x) in a state space grid.

perturbation." If the adolescent's state self-esteem level often changed at the same time as a change in parental interaction style and was not variable while this parental interaction style was expressed, we referred to this parent's interaction styles as having a high level of parental perturbation.

State space grid methodology was used to map these two processes (SSG; Hollenstein, 2013; [47]). This was done in the program GridWare 1.1 (Lamey et al., 2004). SSGs portray the dynamics of two streams of events across time. This is most commonly done for the streams of behavior between two individuals, but can be done for any two variables that have synchronized streams of categorical data. The sequence of events that occur between the variables is plotted as it proceeds in real time on a grid representing all possible event combinations. Each cell of the grid represents the simultaneous intersection of each variable. The events for one variable are plotted on the x-axis, and the events for the second variable are plotted on the y-axis. Any time there is a change in either variable, a new point is plotted in the cell representing that joint event and a line is drawn connecting the new point and the previous point. Thus, the grid represents the sequence of the system's events [69]. This is illustrated in Figure 6, with hypothetical variable 1 (with two possible events) on the y-axis and variable 2 (with five possible events) on the x-axis. Each dot represents the intersection between variables 1 and 2 at each moment, with four events plotted across time. The arrows represent the succession of steps, beginning with the dot on the left.

In the current study, we used SSGs to examine the within-individual dynamics between SSE and self-esteem attractors and between SSE and parental interaction styles

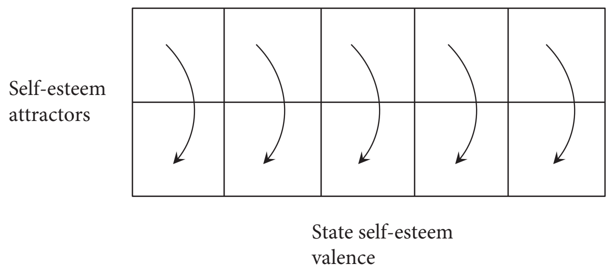

Figure 7: The intercell difference between an individual's two attractors was calculated for each level of state self-esteem. If the intercell difference was high across all levels of state self-esteem, this indicated that each level of state self-esteem predominantly occurred while one (but not both) self-esteem attractors were expressed (i.e., high temporal correspondence). If the intercell difference was low, it indicated that this specific range of state self-esteem levels was experienced irrespective of the self-esteem attractor that is expressed (i.e., low temporal correspondence).

to determine whether variability between the two streams temporally corresponded. We therefore plotted the sequence of state self-esteem events on the x-axis against the sequence of higher-order patterns (separately for trait self-esteem attractors and for parental perturbations) on the y-axis. We thus mapped the temporal correspondence with state self-esteem variability for the sequence of self-esteem attractor states and for parental interaction styles separately.

Because SSGs required ordinal data, it was necessary to first transform the smoothed state self-esteem time series (shown in Figure 4) into ordinal data. In line with other studies that use SSGs [69], we collapsed our continuous data into five categories: very low = 1, low = 2, medium = 3, high = 4, and very high = 5. Note that the absolute values of state self-esteem are not part of the analysis, as we only examined the temporal structure of transitions from one level to the other. Changing the scale for the use of SSGs therefore did not change the conclusions that can be drawn.

Aside from providing a graphical display of the stream of events between two variables across time, the SSG method also quantifies characteristics of the stream of events. We used the SSG to count the frequency of events in all possible cells for each individual's grids. Each individual had two grids: one for SSE (x) against self-esteem attractors (y) and one for SSE (x) against parental interaction styles (y). We used these frequencies to determine the extent to which each level of state self-esteem (x = very high, high, medium, low, very low) temporally corresponded with each higher-order cluster (y = self-esteem attractor 1 or self-esteem attractor 2 and parental interaction style 1 or parental interaction style 2). For each individual, the total number of events for self-esteem attractor 2 was subtracted from the total number of events for self-esteem attractor 2 within each level of state self-esteem (see Figure 7). The same was done for the grids with SSE against parental interaction styles. These frequencies were made proportionate to the total number of events for each level of state self-esteem (x).

The formal calculation for temporal correspondence between state self-esteem variability and high-order variability is shown in Formula (2). When calculated based on the temporal correspondence of SSE with self-esteem attractors 1 and 2, it refers to *self-esteem attractor constraint*, when calculated based on the temporal correspondence of SSE with parental interaction styles 1 and 2, and it refers to *parental perturbations*.

$$\text{Self-esteem attractor constraint OR parental perturbations} = \sum_{i=1}^{5} \left(\frac{x_i y_1 - x_i y_2}{x_i y_1 + x_i y_2} \right), \quad (2)$$

where x is the number of times that state self-esteem occurred for each cell on the x-axis (and where i = the level of state self-esteem; i.e., $i = 1, 2, 3, 4, 5$), and where y is the number of times that each higher-order cluster occurred for each cell on the y-axis (where y_1 = self-esteem attractor 1 or parental interaction style 1 and y_2 = self-esteem attractor 2 or parental interaction style 2, depending on which is being calculated). Temporal correspondence with SSE ranges from 0 to 1, where 0 = no correspondence and 1 = perfect correspondence.

To illustrate the above calculation of temporal correspondence, if "very low" state self-esteem events ($x = 1$) frequently occurred while *both* self-esteem attractors 1 and 2 were expressed ($x = 1$ events were dispersed across both self-esteem attractor 1 and self-esteem attractor 2), this would indicate that there was low temporal correspondence between "very low" state self-esteem and any one specific attractor. As such, this indicates that self-esteem attractors 1 and 2 are weak attractors. In contrast, if "very low" state self-esteem events ($i = 1$) frequently occurred with only *one* of the two attractors (e.g., $x = 1$ events were only found in self-esteem attractor 1), this would indicate that there was high temporal correspondence between "very low" state self-esteem and self-esteem attractor 1. As such, this suggests that self-esteem attractor 1 is a strong attractor. While this example only uses $x = 1$, this was applied for all levels of state self-esteem (1–5) and for each individual separately.

Figures 8(a) and 8(b) are examples of empirical state space grids for two individuals (i.e., output from the GridWare program). The grids portray the sequences of events for self-esteem attractors (y) against SSE variability (x). Figure 8(a) shows an adolescent with a relatively high level of self-esteem attractor constraint (0.46), and Figure 8(b) shows an adolescent with a relatively low level of self-esteem attractor constraint (0.11).

Figure 8(a) shows that the two self-esteem attractors differentiated between levels of state self-esteem valence, where self-esteem attractor 1 exclusively occurred at the same time as high and very high state self-esteem levels (i.e., cells 4 and 5), while self-esteem attractor 2 exclusively occurred at the same time as very low and low state self-esteem levels (i.e., cells 1 and 2). With regards to our earlier formula for calculated self-esteem attractor constraint, this means that the absolute difference in the number of observations between self-esteem attractor 1 ($x_i y_1$) and Self-esteem attractor 2 ($x_i y_2$) is relatively high, resulting in a high absolute level of self-esteem attractor constraint (0.46). In contrast, Figure 8(b) shows that the two attractors did not

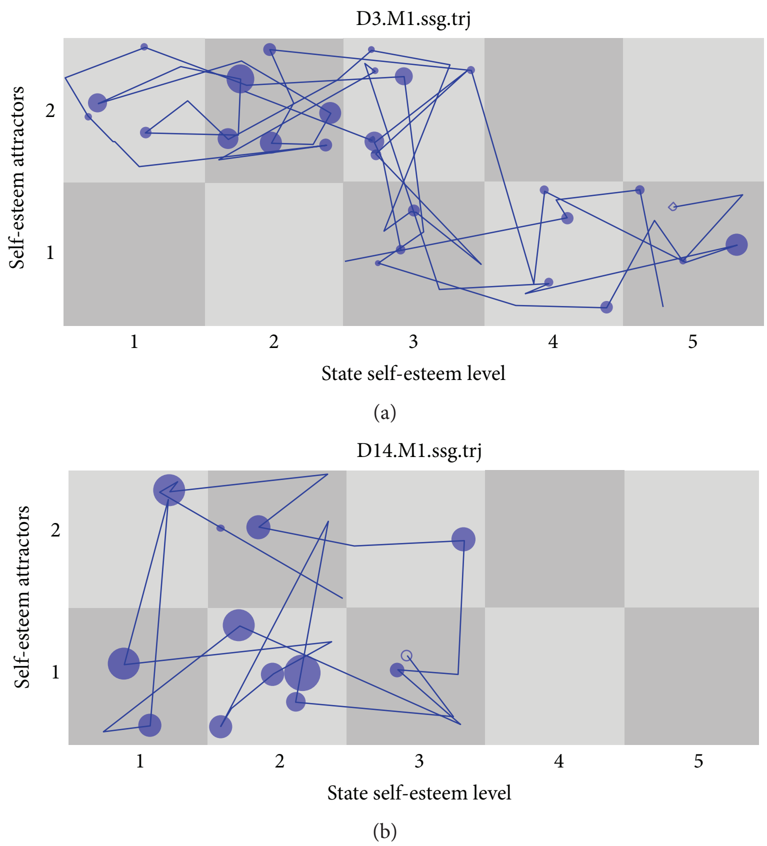

FIGURE 8: Two examples of state space grids from our data portraying the time series for self-esteem attractor expression (y-axis) against the time series for state self-esteem (x-axis). The lines indicate direction of movement between events, and circles indicate duration of events. (a) Illustrates an individual with a high level of self-esteem attractor constraint, while (b) illustrates an individual with a low level of self-esteem attractor constraint.

differentiate between levels of state self-esteem valence, where self-esteem attractors 1 and 2 corresponded with the same state self-esteem levels: very low, low, and medium (i.e., cells 1 to 3). This means that the absolute difference in number of observations between self-esteem attractor 1 ($x_i y_1$) and self-esteem attractor 2 ($x_i y_2$) is relatively low, and a low absolute level of self-esteem attractor constraint (0.11).

3.3. Part 3: Testing the Interplay between Attractor-Like Patterns of Self-Esteem and Parental Perturbations. What was of interest in this step of the analysis was the within-individual comparison of self-esteem attractor constraint (i.e., temporal correspondence of self-esteem attractors with SSE variability) relative to parental perturbations (i.e., temporal correspondence of parental interaction styles with SSE variability).

We split the sample of adolescents into two (based on a median split of the level of self-esteem attractor constraint) to examine the within-individual difference scores (between the level of temporal correspondence with self-esteem attractors and with parental interaction styles) for adolescents with relatively "strong" self-esteem attractors compared to adolescents with relatively "weak" self-esteem attractors. We called the group of adolescents with "strong" self-esteem attractors profile 1, and we called the group with "weak" self-esteem attractors profile 2.

Within-individual levels of temporal correspondence with SSE are shown for self-esteem attractors and parental interaction styles, for profile 1 and profile 2, in Figure 8 below. The figure shows that the within-individual differences were in the expected direction for both profile 1 and profile 2. Specifically, for all adolescents in profile 2 (i.e., relatively "weak" self-esteem attractors), individual levels of parental perturbations were stronger than individual levels of self-esteem constraint were. This is in line with the SOSE conceptualization that state self-esteem will be more vulnerable to perturbations from the social context for individuals with weaker self-esteem attractors. The differences were in the opposite direction for profile 1: Figure 9 shows that all adolescents in profile 1 (i.e., "strong" self-esteem attractors), except for one, show higher levels of temporal constraint for self-esteem attractors relative to parental interaction styles. This corresponds with the SOSE suggestion that state self-esteem will be less perturbed by changes in the social context for individuals with stronger self-esteem attractors.

To provide a confirmatory test of the above differences, we used the Monte Carlo bootstrapping method. This method compares the real data to permutations of the data based on resampling. With each resample, a specific property of the real data is compared to that in the sampling distribution, where the null hypothesis is that there is no difference. In the current study, we used 5000 permutations of the data.

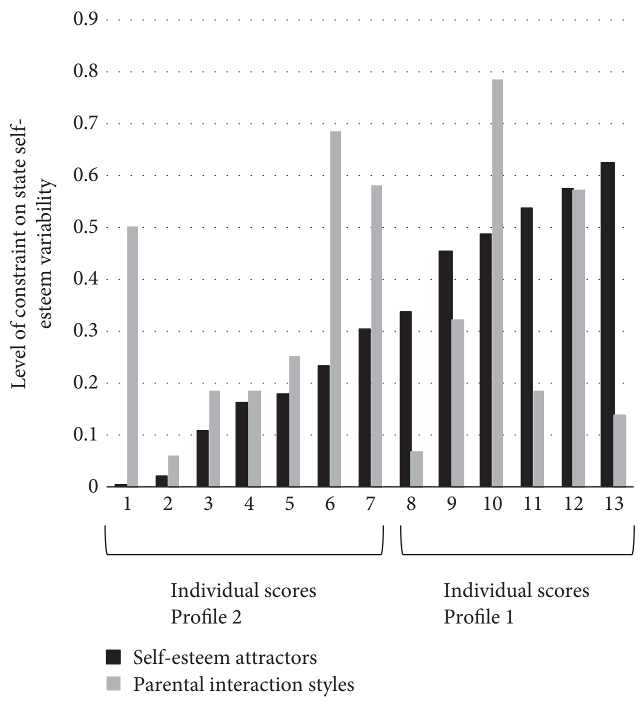

Figure 9: Individual levels of temporal correspondence between SSE and self-esteem attractors with SSE and parental interaction styles.

The Monte Carlo analysis does not rely on assumptions about the population from which the data came (such as normality or homoscedasticity), making it a suitable method for small sample sizes such as ours. Because assumptions about the population are not made, the aim of the analysis is not to estimate characteristics about the general population. Instead, the aim is to ascertain if this configuration of data could have occurred randomly or not. The conclusions drawn are thus related to the sample itself and the implications that this has for the theory that we are interested in.

First, we tested the hypothesis that the average self-esteem attractor constraint for profile 1 ($M_{\text{self-esteem attractor constraint}} = 0.50$ (SD = 0.09)) is larger than for profile 2 ($M_{\text{self-esteem attractor constraint}} = 0.15$ (SD = 0.10)), with $p = 0.001$. The Monte Carlo method was also used to test the hypothesis that the average self-esteem attractor strength is larger than the average parental perturbations in profile 1 ($M_{\text{self-esteem attractor constraint}} = 0.50$ (SD = 0.09) > $M_{\text{parental perturbations}} = 0.34$ (SD = 0.10)), while the average parental perturbations is larger than the average self-esteem attractor strength in profile 2 ($M_{\text{parental perturbations}} = 0.35$ (SD = 0.21) > $M_{\text{self-esteem attractor constraint}} = 0.15$ (SD = 0.10)), with $p = 0.012$. Therefore, the two profiles of attractor constraint were significantly different in our sample, and these two profiles show significantly different relationships with the effect of parental perturbations.

4. Discussion

In this study, we examined the interplay between adolescents' intrinsic dynamics of self-esteem and extrinsic forces at the micro level (i.e., from moment to moment). First, with regards to the intrinsic dynamics, we found that our sample of adolescents showed large variation regarding how much constraint adolescents' "self-esteem attractors" had on their state self-esteem variability, indicating different levels of attractor "strength." The sample could be characterized by a "strong attractor" profile and a (significantly different) "weak attractor" profile. Our measure of self-esteem attractor constraint was based on the extent to which transitions to and from specific self-esteem attractor-like patterns occurred at the same time as specific changes in state self-esteem valence. For this, we used observable indicators of adolescents' self-esteem—self-affect and autonomous actions—during parent-child interactions.

This first finding provides proof of concept of "self-esteem attractors," as described in the Self-Organizing Self-Esteem (SOSE) model and for individual differences in the landscapes that these attractors form. Specifically, the SOSE model draws from the complex dynamic systems perspective and suggests that self-esteem is best conceptualized as a system of nested self-esteem levels (lower-order processes such as state self-esteem and higher-order processes of recurring patterns, i.e., attractors). From this model, individuals have self-esteem attractors that "attract" lower-order processes (i.e., state self-esteem), where each self-esteem attractor within an individual's landscape pulls this lower-order process in a different direction.

While previous studies have found evidence for intrinsic dynamics of self-esteem [15–17, 43], the SOSE model suggests that these intrinsic dynamics specifically stem from the pull by various self-esteem attractors on state self-esteem variability. In this way, self-esteem is seen as a kind of habit or tendency that the individual is more likely to fall into with regard to their moment-to-moment experiences of self, compared to alternative potential tendencies.

The SOSE model suggests that self-esteem attractors can become entrenched over time if they are frequently "visited" and that individuals will thus differ in how entrenched their self-esteem attractors are. Individuals with more entrenched self-esteem attractors experience more constraint (i.e., more pull) on their state self-esteem processes. Our sample supports this prediction regarding individual differences in how entrenched self-esteem attractors are, as indicated by varying levels of constraint on state self-esteem. The variation found in our sample also attests to the sensitivity of our measure of "attractor constraint."

This finding is in line with previous studies that found individual differences in how stable self-esteem is and how abruptly self-esteem shifts, where more unstable self-esteem is related to not having a clear sense of self that provides a stable frame of reference for experiences of self (i.e., low *self-concept clarity*; Nezlek and Plesko, 2001; [16]). From a complex dynamic systems perspective, this can be interpreted as indicating that a lack of clear sense of self indicates weak attractors, as these do not provide much stability to individuals' experiences of self [16, 26, 70].

These previous studies examined self-esteem variability as one process and related characteristics of this process to levels of self-concept clarity. While self-concept clarity was theorized to indicate something about individuals' attractor landscapes (where low self-concept clarity may be conceptually similar to having weak attractors; [16]), our study is the first to study the moment-to-moment association between two nested, but separate, self-esteem processes: self-esteem attractors and state self-esteem variability.

Our second finding provides convergent validity for the conceptualization of "self-esteem attractors." If the higher-order patterns measured in our study can indeed be conceptualized as "attractors," these patterns should demonstrate additional properties of attractors. We found evidence of this. Specifically, the self-esteem attractors that were characterized as relatively *strong* versus *weak* (based on their intrinsic dynamics) demonstrated a key property of *strong* versus *weak* attractors, respectively, based on their interplay with extrinsic forces. We found that potential external perturbations (stemming from changes in parental interaction styles) on state self-esteem were *weaker* than the intrinsic dynamics (i.e., constraint of self-esteem attractors on state self-esteem) for adolescents in the profile characterized by strong self-esteem attractors. In contrast, potential external perturbations (stemming from changes in parental interaction styles) on state self-esteem were *stronger* than the intrinsic dynamics (i.e., constraint of self-esteem attractors on state self-esteem) for adolescents in the profile characterized by weak self-esteem attractors. This provides direct support for the prediction that "strong" attractors allow for fewer perturbations from extrinsic forces, while "weak" attractors allow for more perturbations on state self-esteem from extrinsic forces [19].

This is an important finding, as it has been previously shown that daily experiences of self-esteem show a temporal pattern that suggests a pull between preservation of previous levels and adaptation in the direction of new information [43]. This previous research suggests that attractor states may underlie the preservation of previous levels and that contextual perturbations may underlie the adaptations in new directions [43]. However, these underlying mechanisms were not explicitly operationalized or tested.

Our study thus expands upon previous research by explicitly measuring attractor constraint and studying its temporal association (at the within-individual level) with state self-esteem. As such, this was the first attempt to explicitly test the push and pull between attractor states and contextual perturbations. While taking new methodological steps, our findings thus contribute to a line of emerging research that collectively supports the notion that individuals have attractors of self-experiences and that these attractors can provide stability to individuals' experience of the self, depending on how strong the attractors are [16, 26, 70].

4.1. Implications for the Ontology of Self-Esteem. The current findings are highly relevant for the longstanding debate as to whether self-esteem is best conceptualized as a *stable* trait or a *variable* state [71, 72]. Recent studies are moving this debate away from the "either or" perspective, showing that self-esteem consists of *both* a relatively stable (but slowly evolving) trait element and a variable state element [12, 13, 73]. Our findings are in line with this suggestion and go further by describing the precise nature of the stable component and the variable component as well as the mechanism underlying their relationship.

Specifically, it has long been suggested that state self-esteem fluctuates around a resting "baseline" level [8]. This has important implications for the conceptualization of the stable component of self-esteem and for the variable component. First, the stable component of self-esteem is commonly seen as a baseline level that is informative as a *description* of an individual's central tendency. This is demonstrated when repeated measures of state self-esteem are averaged in order to gain a measure of an individual's "true" level of self-esteem (i.e., of trait self-esteem) [5].

Our findings suggest that the "stable" component of self-esteem is not a resting baseline level, but a *dynamic mechanism*. Self-esteem attractor states provide stability to state self-esteem experiences by attracting future state self-esteem experiences in the direction of previously developed patterns of self-experience. While the quality of these attractor states (e.g., positive or negative self-esteem) can be informative about an individual's self-esteem tendency, our alternative conceptualization suggests that this stable component is more than a description of this tendency.

Next, the common conceptualization of self-esteem has important implications for the conceptualization of the variable component of self-esteem (i.e., state self-esteem). Specifically, it is usually assumed that state self-esteem fluctuations occur in response to "incoming information relevant to relational evaluation" ([9], p. 2). Therefore, state self-esteem fluctuations are seen as a "subjective index or marker of the degree to which the individual is being included versus excluded by other people" ([10], p. 519), where "cues that connote high relational evaluation raise state self-esteem, whereas cues that connote low relational evaluation lower state self-esteem" ([9], p. 2). In short, the cornerstone of the dominant conceptualization of state self-esteem is that variability of state self-esteem is due to external social forces and that each fluctuation indicates characteristics of the immediate social context (e.g., degree of being excluded).

Our findings suggest that, while state self-esteem *is* responsive to the social context (in this case, parental support and affect during interactions), the degree of responsivity may be partly determined by the intrinsic dynamics of self-esteem. State self-esteem variability is thus not just indicative of the "degree to which the individual is being included versus excluded by other people" ([10], p. 519) but also of the strength of an individual's self-esteem attractor states. As such, a negative state self-esteem experience, for example, is not only the result of "cues that connote low relational evaluation" ([9], p. 2), but it is potentially also a result of a pull toward a negative self-esteem attractor.

The interplay between contextual forces and intrinsic forces acting upon state self-esteem has important implications for understanding the role that parents have on adolescents' self-esteem specifically. While it has often been shown that parents have an important influence on adolescents' general level or future development of self-esteem (e.g., [48, 74]), our study contributes to the understanding of the moment-to-moment influence that parents have on adolescents' self-esteem. More specifically, our findings shed light on why some adolescents' self-esteem may be less susceptible to their parents' support or expressed affect than others, depending on how much their own self-esteem attractors are "pulling" on their state self-esteem processes. If adolescents' self-esteem attractors are highly entrenched and have a high level of constraint on their state self-esteem variability, any moderate changes that parents make to their behavior and emotional expressions during interactions may have a limited effect on their child's state self-esteem. Therefore, while parents may be rightly encouraged to interact with their adolescent children in a way that displays more autonomy support and emotional relatedness [48], these efforts may not be met with the expected positive effects on their child's state self-esteem if the child's self-esteem attractors are highly entrenched.

4.2. Limitations and Future Directions. It was beyond the scope of the current study to investigate where individual differences in self-esteem attractor constraint come from. It may be that these differences represent relatively stable individual differences (in line with previous suggestions that individuals differ with respect to how much they base their self-evaluation on others' evaluation, e.g.,; [28, 71]). On the other hand, individual differences may also represent differences in developmental phases of self-esteem.

The SOSE model suggests that individuals' self-esteem attractor landscapes significantly change during important transition phases in life [19]. During this time, old attractors are potentially abandoned (such that they are infrequently visited, making them shallower), and new attractors are beginning to form. During such a phase, the individual's attractor landscape therefore consists of weak attractors, resulting in more variability of lower-order processes [23].

In line with this, it has indeed been shown that state self-esteem becomes more variable during a transition phase [12]. As adolescence is a period of significant change in self-esteem [31, 75], it is likely that adolescence is thus also a period in which self-esteem attractors re-form and thus weakly constrain state self-esteem. Given that our sample consisted of preadolescents, we might expect that the adolescents in our sample already entered a period of significant developmental changes in self-esteem. However, age itself is not a good proxy for developmental transition phases [76]. Therefore, it is more likely that some adolescents had already entered such a transition phase while others had not (yet). This would account for the individual differences in attractor strength in our sample.

Future studies are needed to closely examine the extent to which individual differences in attractor strength are stable individual differences, and in that case, whether these differences are related to differences in how people evaluate themselves (i.e., evaluation based on others' evaluations or not, e.g.,; [28, 71]). It may be that different ways of evaluating one's self somehow prevents the entrenchment of any specific self-esteem attractor. Longitudinal studies are necessary to explore this, as only then is it possible to determine whether attractor states become weaker versus stronger over time, when, and for whom.

In our study of attractor strength, we made no distinction between positive versus negative parental interaction styles. Research shows, however, that the effect of negative events on self-feelings of low self-esteem individuals is smaller than the effect of positive events on self-feelings of high self-esteem individuals [28]. If we assume that self-esteem attractors underlie trait self-esteem, these findings might suggest that individuals with negative self-esteem develop stronger self-esteem attractors. As such, only a small external push in the direction of the attractor (i.e., a small negative event) results in a large drop in state self-esteem. Future research is necessary to examine whether negative self-esteem attractors indeed become more easily entrenched over time and whether this explains a higher reactivity to negative daily events.

In this study, we tested the dynamic interplay between multiple complex dynamic systems principles that have not been previously applied in the context of self-esteem, including attractor constraint and contextual perturbations. As such, our operationalizations of these constructs were based on a marriage between complex dynamic systems theory and self-esteem theory, and not on previously validated measures. As these process concepts are not readily studied in psychology, our study illustrates an initial attempt to do so as thoroughly as possible. Future research should further explore these operationalizations and their validity.

Additionally, the current study did not examine all aspects relevant to a complex dynamic systems conceptualization of attractor landscapes. Specifically, an individual's attractor landscape is characterized by attractors *and* repellers, where repellers define the boundaries between attractors that the system avoids and cannot easily reach (such that a relatively large amount of energy would be required) or maintain (such that a relatively large amount of instability would arise if reached). The current study focuses on attractors because the notion of attractors lends itself more directly to self-esteem theory (i.e., where self-esteem—as a trait—is also characterized as being a specific self-evaluative tendency that an individual is drawn to). For this reason, attractors are also central in the Self-Organizing Self-Esteem model, which provides the foundation for the current study. However, the notion that some experiences of self-esteem are avoided is another area that requires additional research. Wong et al. [26], for example, have explored this by examining highly unstable points of self-evaluation. Future studies are needed to further explore the dynamics of self-esteem repellers, by studying both the energy needed to reach such points and the level of stability observed if those points are reached.

5. Conclusion

The variability of state self-esteem is an important characteristic of self-esteem, but the source of that variability is not well understood. A strength of the current study is the use of real-time dyadic data and time series analyses. This allowed us to investigate the moment-to-moment dynamics between adolescents' state self-esteem variability, the expression of their self-esteem attractors, and parental perturbations. In doing so, we found that the adolescents

Table 1: Examples of self-esteem attractor characterizations for two participants (A and B).

Percentage of time expressed	Participant A SE Attractor 1 (58.2%)	Participant A SE Attractor 2 (41.8%)	Participant B SE Attractor 1 (27.4%)	Participant B SE Attractor 2 (72.6%)
		Test value network characteristics		
Self-affect	17.19	−17.19	9.14	−9.14
Autonomy	−13.47	13.47	17.30	−17.30
Self-experiential incoherence	−10.9	10.9	4.65	−4.65

Note. SE = self-esteem.

demonstrated attractor-like patterns of self-esteem. For some adolescents, these self-esteem attractors were "strong" and for others they were "weak," as defined by the level of constraint that they had on lower-order processes of self-esteem (i.e., state self-esteem). Thus, individuals differed in the nature of their intrinsic dynamics of self-esteem. For adolescents with "strong" self-esteem attractors, we found that parental perturbations on state self-esteem were *weaker* than their self-esteem attractors. For adolescents with "weak" self-esteem attractors, we found that parental perturbations were *stronger* than their self-esteem attractors.

These findings bring us closer to understanding how the process of adolescents' state self-esteem is shaped from moment to moment during parent-child interactions. By explicitly examining the external forces from parents *and* adolescents' attractor constraint acting upon state self-esteem, this study helps to integrate two perspectives on self-esteem: the common approach that stresses the role of social cues [10] and emerging studies that stress the role of intrinsic dynamics [15–17, 26, 43, 77]. As such, this study contributes to more a more nuanced conceptualization of the variable and stable components of self-esteem.

This study provides support for the ontology of self-esteem as a complex dynamic system, and it sets the groundwork for future studies to further explore the mechanisms that underlie self-esteem processes. By empirically illustrating these mechanisms, we hope that our study will encourage researchers in the social sciences to further explore the implications of conceptualizing self-esteem and related concepts (such as personality, attitudes, etc.) from a complex dynamic systems perspective.

Appendix

Figure 5 demonstrates how individuals can differ with regard to the temporal pattern of variability between self-esteem attractors 1 and 2. Aside from the temporal variability between self-esteem attractors, the self-esteem attractors differed in content, both within and between individuals, with regard to the weight of the emotional versus behavioral experiences of self and the positivity or negativity of the various measures. To illustrate, the characterization of the two self-esteem attractors for participants A and B (from Figure 5) are displayed in Table 1. The table shows the percentage of time during which each self-esteem attractor was expressed across the entire dyadic interaction for each individual. The extent to which each self-esteem attractor was characterized by each self-experiential variable is indicated by the *test value* (For more information, see the "Understanding the 'test value' criterion" tutorial provided by Tanagra (http://data-mining-tutorials.blogspot.nl/2009/05/understanding-test-value-criterion.html)).

The test value shows how much weight each component has in determining the expression of that specific self-esteem attractor, where higher absolute values indicate a higher weight. The test value is deduced based on a statistical within-individual test of a comparison of means (the mean value across the entire time series compared to the mean value during the duration in which the specific cluster is active). For each self-esteem attractor, the component with the highest absolute test value is the component that—when experienced (with the relevant valence)—is most likely to trigger the expression of that specific attractor. For example, for participant A, it was likely that self-esteem attractor 1 was triggered when positive self-affect was experienced, given that self-affect had the highest absolute test value (test value = 17.19), and it was likely that self-esteem attractor 2 was triggered when negative self-affect was experienced (test value = −17.19). For participant B, the valence of autonomous self-experiences was most pivotal (test value = 17.30 and −17.30 for self-esteem attractors 1 and 2, resp.).

Because we defined two attractors for each individual, the emergent attractors were triggered by opposing levels of each component (i.e., self-affect, autonomy, and self-experiential incoherence). This can be seen in Table 1, where (within each individual) the test values of the network characteristics for attractor 1 were opposite in valence from those for attractor 2. The absolute values of test values differed between individuals, however, indicating a between-individual difference in weight regarding the various self-experiential components.

Data Availability

Raw video material and Excel files are stored on the secure network drive of the University of Groningen (UWP Data Storage), to which only I and the data manager have access. This storage facility is protected and secure and is compliant with the University of Groningen Research Data Policy. Anonymous data can be made available for reuse through DANS (Data Archiving and Networked Services) upon request.

Ethical Approval

All procedures were in accordance with the ethical standards of the Ethical Committee Psychology of the University of Groningen in the Netherlands.

Consent

Informed consent was obtained from all individual participants in the study.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this article.

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Research Article

The Development of Talent in Sports: A Dynamic Network Approach

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Understanding the development of talent has been a major challenge across the arts, education, and particularly sports. Here, we show that a dynamic network model predicts typical individual developmental patterns, which for a few athletes result in exceptional achievements. We first validated the model on individual trajectories of famous athletes (Roger Federer, Serena Williams, Sidney Crosby, and Lionel Messi). Second, we fitted the model on athletic achievements across sports, geographical scale, and gender. We show that the model provides good predictions for the distributions of grand slam victories in tennis (male players, $n = 1528$; female players, $n = 1274$), major wins in golf (male players, $n = 1011$; female players, $n = 1183$), and goals scored in the NHL (ice hockey, $n = 6677$) and in FC Barcelona (soccer, $n = 585$). The dynamic network model offers a new avenue toward understanding talent development in sports and other achievement domains.

1. Introduction

In 1869, Francis Galton published his work on the genetics of genius, in which he claimed that eminent individuals are born with the potential to excel in the future. He based this conclusion on his observation that elite performance tends to run in families at much higher rates than could be expected based on chance [1]. A few years later, De Candolle wrote a book in which he stated that environmental resources (e.g., family, education, and facilities) are the major factors explaining the emergence of excellence [2]. Galton later contrasted their viewpoints in the terminology of nature and nurture [3], which formed the starting point of the famous nature-nurture debate in psychology [4]. Now, over a century later, it remains a major challenge to understand how individual trajectories of talent development are shaped by the complex interplay between nature and nurture factors. A related and important question is why only very few individuals are ultimately able to demonstrate exceptional performance. Here, we briefly discuss different past and current perspectives, after which we explain that a novel dynamic network approach provides the theoretical principles and analytical tools to understand how talent develops. In doing so, we primarily focus on the domain of sports, in which talent development has received much attention from researchers, and in which rich sets of empirical data are available.

In order to define the kind of model that captures the process of talent development, the first important step is the conceptualization of talent and related concepts. Talent can be defined as an individual's *potential* or capacity to excel in a particular domain that requires special skills and training [4]. The individual's potential is a condition specified by all available factors contributing to the actual growth of a particular ability [4, 5]. An individual's *ability* can then be defined as the manifest or actualized potential. This ability can vary from very low to exceptionally high, but actualized talent typically corresponds to the high ability range [4, 6, 7]. Although ability is not directly observable, an individual's performance accomplishments, such as winning sports tournaments, is a stochastic function of ability that *can* be measured. Proceeding from this conceptualization, one can derive that talent *development* is the process through which potential turns into manifest abilities, which may result into measurable demonstrations of elite performance [4, 8].

So far, research on talent development has primarily centred around the question: How much do particular genetic and nurturing factors contribute to the development of elite performance [9–12]? Although some researchers have emphasized the importance of one particular factor, such as genetic endowment [13] or deliberate practice [14, 15], researchers have now reached consensus that various nature and nurture factors contribute to the development of talent [10–12, 16, 17]. The current challenge is to be able to answer the question: What kind of model or mechanism can account for the way in which combinations of nature and nurture variables shape the process of talent development, which for some athletes result in elite performance achievements? In the behavioural sciences, the standard model describes momentary associations between variables across samples that are large enough to represent the population of interest (e.g., elite athletes in a particular sport). The most obvious of such models is a regression model, which explains the interindividual variability of abilities, skills, or performances on the basis of the sum of factors that are associated to the athletic ability at hand. For instance, in a linear regression model, a level of ability, A, is the sum of levels of constituent components:

$$A = \alpha + \beta x + \gamma y + \cdots, \tag{1}$$

where the variables x, y, and so forth are the predictors, such as genetic endowment, physical factors, psychological factors such as commitment, and environmental factors such as family support, with α, β, and γ moderating the effects of the variables.

Following the standard model, scientific projects across countries and types of sports have put a major focus on finding the physical, technical, tactical, psychological, practice, and environmental variables that distinguish groups of elite athletes from groups of sub- or nonelite athletes [18–24]. Outcomes of these projects increasingly suggest that the model underlying talent development is *not* a linear, uniform model that holds within samples of athletes. This suggestion is in accordance with the so-called ergodicity problem, according to which a model based on group data only generalizes to a model of individual processes if very specific conditions apply, which are hardly ever met in the behavioural and social sciences [25, 26]. For instance, a statistical model based on a typical sample of a great number of individuals may take the form of a linear regression model, describing the codistribution of the observations in the space of variables. Every individual model, on the other hand, is likely to take the form of idiosyncratically, dynamically coupled variables, which associate over time in ways that are fundamentally different from the statistical group model. When looking more closely at individual processes of talent development, research has increasingly shown that (i) an athlete's ability level as well as possible determinants (e.g., physical qualities and commitment) change over time; (ii) genes, the environment, and other physical and psychological factors are intertwined in complex ways; and (iii) there is no average, linear developmental trajectory that holds across athletes. In addition, contrary to the assumption of standard models, the distribution of talent across the population is considered to be *non*-normal [10, 16, 27, 28].

To exemplify the four properties mentioned above, first, evidence for the dynamic development of talent can be derived from research tracking athletes' performance histories [19], reports on athletes' scores on correlates of sports performance (e.g., intermittent endurance capacity of soccer players [29]), and in-depth qualitative investigations [20]. Second, the property that genes, the environment, and other (physical and psychological) factors are intertwined is increasingly acknowledged in behavioural genetics and epigenetic models [28, 30]. Nature and nurture are thus inseparable in the development of certain traits or qualities, including sports talent. This is consistent with the idea that even environmental factors that are considered as signs of nurture, such as parental support, also carry a genetic component, given that parents' genetic make-up is partly responsible for their creation of a stimulating home environment to develop talent [31–33]. Third, the complex interplay between nature and nurture factors may take different forms for different athletes, and researchers have shown that the road to the top is hardly ever a straight road [19, 34]. For instance, a study among elite Australian athletes showed that most athletes underwent different (nonlinear) trajectories from junior to senior, with less than 7% of all athletes demonstrating a pure linear trajectory [19]. A comparable conclusion could be drawn from longitudinal research projects in soccer, field hockey, basketball, artistic gymnastics, tennis, and speed skating, conducted in the Netherlands. In their studies, the researchers primarily searched for underlying predictors at the group level, but later concluded that athletes have their own unique developmental patterns that lead to excellent performance [35]. There are two kinds of explanations for these unique pathways, which may co-occur. The first is that the relationships between underlying variables are not static and linear but rather dynamic and complex [4, 7, 9, 16, 27, 36], and the second is that certain predictable or unpredictable events may occur that affect the further developmental trajectory of the individual athlete [20, 34, 37, 38]. One example of a predictable event is the transition from youth to professional, which can be a critical period in an athlete's development [19, 38, 39]. Unpredictable events, such as trauma, may also occur and have a considerable impact on the athlete's further trajectory [17, 20, 34, 38, 40, 41].

Finally, the fact that the distribution of talent across the population is not normal has been stressed repeatedly, mostly by Simonton [4, 42, 43]. Across the population, talent would be skewed with a heavy tail to the right. Although it is virtually impossible to directly measure talent (i.e., potential), it is possible to measure the expressions of an athlete's ability (i.e., actualized talent) in terms of performance achievements. Assuming that the measurable achievements of athletes provide an indication of their actualized talent, research has indeed shown highly right-skewed distributions in different sports including American football, cricket, baseball, basketball, soccer, swimming, track and field, car racing, tennis, and skiing [16, 44–48]. These highly skewed distributions are often characterized by so-called power laws, in which the exceptional athletes can be found in the right

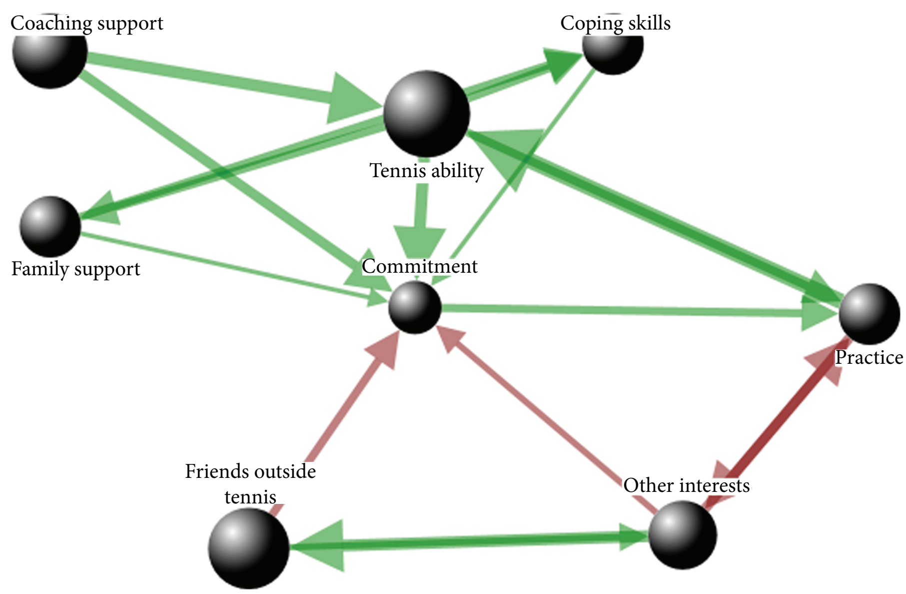

Figure 1: Fictive illustration of a talent network. In this case, the network includes an imaginary tennis player's ability and other personal and environmental supporting and inhibiting factors that may differ across individuals. Green arrows represent positive influences, and red arrows represent negative influences. The sizes of the components reflect their level at a certain moment, and the thickness of an arrow is proportionate to the strength of influence. Note that the displayed network is a simple, speculative snapshot and that the network is dynamic and idiosyncratic in reality.

tail. This entails that, across the sample of athletes in any sports, there are very few who ultimately reach exceptional achievements at the professional level [20, 46, 49]. For instance, among the elite swimmers, Michael Phelps has won an incredible number of 28 Olympic medals whereas the great majority of professional swimmers never won an Olympic medal.

To advance the modelling of talent development, one should define the principles that can explain the properties above, driven by assumptions about the definition of talent and the nature of developmental processes. This means that talent should be modelled as a potential that develops through complex nature-nurture interactions [4, 7, 10, 32]. In addition, the model should account for the fact that (i) there is a potential that can grow and can be actualized, (ii) there are supporting and inhibiting factors that change across time, (iii) nature and nurture factors are intertwined and shape each other, and (iv) this developmental process is different for different athletes [4, 7, 10, 16, 27]. Based on these requisites, we propose that talent development can be understood from the perspective of dynamic networks (Figure 1).

In the 2000s, applications of different kinds of network models have become prominent across different scientific domains, including physics, economy, biology, and the social sciences [50]. The difference between dynamic network models and standard models is that the latter focus on associations between specific variables across a particular population (e.g., the association between commitment and performance in the population of soccer players [24]), whereas the dynamic network model focuses on the potentially explanatory properties of a dynamic network structure per se. Dynamic network models allow modelling of individual trajectories, and by modelling a representative sample of individual trajectories, the dynamic network model also offers a model of a population. Establishing a dynamic network model thereby lays the groundwork for future studies of person-specific network structures, in which the nature of the relevant network components can be specified. A key focus of the current article is to reveal what a basic dynamic network model of talent development may look like, validated by data from different sports.

The specific network model we present here is inspired by dynamic systems applications to human developmental processes [51–54]. Mathematically speaking, we proceeded from an extended logistic growth equation, according to which quantitative changes in developmental variables should be understood on the basis of dynamic relationships with other variables that are themselves subject to change [52, 53, 55, 56]. Here, talent is considered as a potential in terms of a mathematically defined growth, and ability is the actual level of a variable at a particular moment in time. The ability variable is embedded in a set of (changing) interconnected variables, defined as *connected growers*. The growers include stable resources, which correspond to the (epi)genetic contribution that may differ for different variables and different individuals [4, 7]. Furthermore, the network is a directed causal graph, which in most cases will be cyclic. The interactions among the variables in the network have a particular "weight" and can be direct but also indirect (e.g., if the athlete's ability positively affects the support provided by the parents, which in turn positively affects the athlete's coping skills, the athlete's ability and coping skills are indirectly connected; see Figure 1).

These network properties can be mathematically defined as follows:

$$\left\{\begin{array}{c} \dfrac{\Delta L_A}{\Delta t} = \left(r_{L_A} L_A \left(1 - \dfrac{L_A}{K_{L_A}}\right) + \displaystyle\sum_{v=1}^{v=i} s_v L_A V_v\right)\left(1 - \dfrac{L_A}{C_A}\right) \\ \dfrac{\Delta L_B}{\Delta t} = \left(r_{L_B} L_B \left(1 - \dfrac{L_B}{K_{L_B}}\right) + \displaystyle\sum_{v=1}^{v=j} s_v L_B V_v\right)\left(1 - \dfrac{L_B}{C_B}\right) \\ \cdots \\ \cdots \\ \cdots \end{array}\right\}, \tag{2}$$

where $\Delta L_A/\Delta t$ corresponds to the change of the variable, K is the stable (genetic) factor, r is the growth rate associated with the stable factor, V corresponds to the other variable components in the network to which the component in question (e.g., L_A) is connected, and s represents the growth rate associated with the variable, supportive or inhibitive factors in the form of connection weights in the network. The C parameter corresponds to the limits of growth of a particular variable (i.e., the absolute carrying capacity), the specification of which is more important than its exact value [16]. This means that the function of the C parameter is to keep the variables within realistic (e.g., biophysical) limits, in the unlikely mathematical possibility that too many relationships are strongly positive and drive the system into an exponential explosion. The extended logistic growth equation gives rise to different, often nonlinear forms of development [16, 52, 53], which are typically observed in the domain of sports [9, 19, 27, 37].

In order to account for events, such as a transition from youth to professional, it should be possible to model a singular perturbation to an athlete's ability level around the transition and expose him or her to new challenges and environments [36, 57, 58]. Following this transition, athletes may reach achievements or not (e.g., winning professional tournaments), which can be modelled by embedding a product model in the network model [16]. One such model is the ability-tenacity model, which is particularly relevant in domains where perseverance, commitment, and devotion are important [45], such as sports [9, 17, 24, 36]. This model also takes into account that the attainments of elite achievements are a function of a "chance" factor, which is typical for sports [35, 59, 60]. The specific formula to calculate an achievement of an athlete at each time point (P_t) therefore equals

$$P_t = \varphi L_t T_t, \tag{3}$$

where φ is the likelihood parameter, L_t is the ability variable in the network, and T_t is the tenacity variable. Importantly, as the ability and tenacity components are directly and indirectly connected with the other network components, the resulting accomplishments are not just the result of these two variables, but are a stochastic function of the interaction-dominant network dynamics in which ability and tenacity are embedded.

In this study, we aimed to test whether a dynamic network model provides a valid theoretical foundation of talent development. Therefore, we simulated athlete-networks based on (2) and compared the outcomes of the simulations with current knowledge based on the extant literature and archival data that we collected. First, in its basic form, the model should generate the individual, nonlinear developmental trajectories for different athletes and include youth-to-professional transition events [9, 19, 27, 35]. Apart from the ability-development of the athletes, the model should be able to generate performance achievements that are a function of ability, tenacity, and a chance factor [49, 59, 60]. Ultimately, among the simulated athletes, only very few should demonstrate achievements that are disproportionally exceptional within the athletic population, as evidenced by a power law distribution [16, 46].

To empirically check the validity of the dynamic network model, we compared the model predictions based on computer simulations with data we collected from two major individual sports (i.e., tennis and golf) and two major team sports (i.e., (ice) hockey and soccer). More specifically, we compared the model predictions with cases of professional athletes (Federer, Williams, Crosby, and Messi) and with the distributions of performance attainments across sports, gender, and geographic scale (from worldwide to local).

2. Materials and Methods

2.1. Archival Data. For this study, we collected archival data from elite tennis players, golf players, (ice) hockey players, and soccer players. In tennis, the number of tournament victories is a direct indicator of a player's achievements. In order to secure an even level of competition across the tournaments and to have comparable datasets for male and female players, we focused on the grand slam tournaments. Comparable to winning a grand slam in tennis is winning a major in golf. Major tournaments also host the highest-ranked players at the given point in time. Another parallel with tennis grand slams is that we can consider both male and female athletes for this sport.

Hockey is a team sport, in which six players are on the field for each team. Of these six players, one is the goaltender and the other five are so-called skaters. Due to the dynamic of the game and the relatively small rink size, each skater is involved in attacking as well as defending. This provides every skater with the opportunity to score goals. Since a team needs to score goals in order to win, scoring is a measurable expression of a player's ability. We focus on the National Hockey League (NHL), USA, which is the highest level hockey competition worldwide. Similar to hockey, to determine performance achievements in soccer, we focus on the goals scored by field players.

To examine individual achievement trajectories, we zoomed into a few elite athletes with exceptional (measurable) achievements. These athletes were Roger Federer, who won an exceptional number of 18 grand slam titles in male tennis at the time of data collection, Serena Williams, who won an exceptional number of 23 grand slams in female tennis, Sidney Crosby, who scored an exceptional number of 338 goals in the NHL, and Lionel Messi, who scored an exceptional number of 312 league goals for FC Barcelona. In addition, we determined the population distributions of performance achievements in tennis, golf, hockey, and soccer. For tennis, we examined the distributions of grand slam titles for male ($n = 1528$) and female players ($n = 1274$). The samples included all players who played at least one single's match in a grand slam tournament since the start of the open era of tennis tournaments (i.e., 1968) until present. Second, we focused on golf major titles for male ($n = 1011$) and female players ($n = 1183$). In order to have a homogeneous and comparable timeframe between men and women, the male count was restricted to the years 1968 (the year ladies major golf tournaments started) until present. The samples included all players who participated in at least one major. In the case of hockey, every skater ($n = 6677$, all male) who ever played in the National Hockey League (NHL), USA, until 2016, was taken into account. Finally, for soccer, we considered all field players ($n = 585$, all male), who played for FC Barcelona in the first Spanish Division since 1928.

The data for the different sports were retrieved from the sports' official websites or the official website tracking the statistics of that sport. The data for tennis were collected through the Association of Professional Tennis' website (http://www.atpworldtour.com, accessed at 16-02-2017) and the International Tennis Federation's website (http://www.itftennis.com, accessed at 17-02-2017); for golf through the Professional Golfers' Association of America's website (http://www.pgatour.com, accessed at 17-04-2017); for hockey through official National Hockey League's website (http://www.nhl.com, accessed at 21-02-2017); and for soccer through the La Liga website (http://www.laliga.es accessed at 22-02-2017).

2.2. Dynamic Network Model Settings. The dynamic network model was implemented in Visual Basic that runs under Microsoft Excel, which allowed us to simulate developmental trajectories of individual athletes. Table 1 shows the default settings of the parameters that we used in order to simulate athletes' dynamic networks. These default settings correspond to the initial values of the parameters in (2), and the model further defines a probability of .25 that two components are directly connected, within a network consisting of 10 variables. This probability and the size of the network are defined a priori based on a previous theoretical paper on modelling excellent human performance [16]. The model corresponds to a neutral model, which means that the weights are on average zero, with a symmetrical distribution towards negative and positive values. In the network, we arbitrarily defined node 3 as the ability variable and node 4 as the tenacity variable.

In addition to the default settings that suffice to run simulations of the basic network, we inserted a transition from youth to professional. In order to model this, we applied a "perturbation" to the ability variable (i.e., node 3) at step 300, which in the simulation marks the transition point. More specifically, we modelled a drop around the transition

Table 1: Default parameter values used for the dynamic model simulations.

Parameter	Average	Standard deviation
r (growth rate)	0.05	0.01
s (connection weight with other variables)	0	0.02
K (stable resources—genetics)	1.00	0.15
Connection probability with other variables	0.25	—
	Minimum	Maximum
L (initial level)	0	0.05
Time of initial emergence of a variable	1.00	350.00
C (carrying capacity)	10.00	25.00

($M_{\text{decrease}} = 0.65$, SD = 0.15), and we let three (out of the ten) variables enter the network around the transition period. The latter corresponds to the fact that athletes likely face new challenges and deal with new factors that might negatively or positively dynamically relate to their ability [20, 37].

Mathematically speaking, the parameters that we defined are dimensionless numbers. This means that they are numbers that do not directly correspond with the dimensionality of specific physical or psychological properties. The parameters are ratio numbers that specify a particular ratio or proportion of effect of one component on other components and on itself. The population described by the model is represented in the form of hypothetical distributions of these parameter values. An individual in this population is represented by any combination of parameter values randomly drawn from these distributions. The empirical verification of the dynamic network model is then based on the following predictions: (1) in any representative sample of parameter combinations, we will find resulting individual trajectories that correspond with observed individual trajectories of athletes, and (2) any representative sample of parameter combinations will generate a population of individual trajectories, the general properties of which correspond with the properties of an observed population of athletes.

In order to model the athletes' achievements, we connected the dynamic network model with a product model. The likelihood that an achievement was generated for an athlete was based on the ability level, level of tenacity, and a likelihood parameter φ (see (3)) [45]. Because it is easier to score goals in hockey and soccer than it is to win grand slams or majors in tennis and golf, the φ parameter had the highest value in hockey ($\varphi = 0.004$), followed by soccer ($\varphi = 0.002$), and then by golf and tennis ($\varphi = 0.0002$). Furthermore, in hockey and soccer it is possible to generate multiple achievements (i.e., goals) at a single time step, which is not possible for the achievements in terms of grand slam and major titles in golf and tennis. Therefore, the maximum number of products per time step was set to 3 in hockey and soccer and to 1 in golf and tennis.

The default parameter settings that we used for the simulations of populations of tennis players, hockey players,

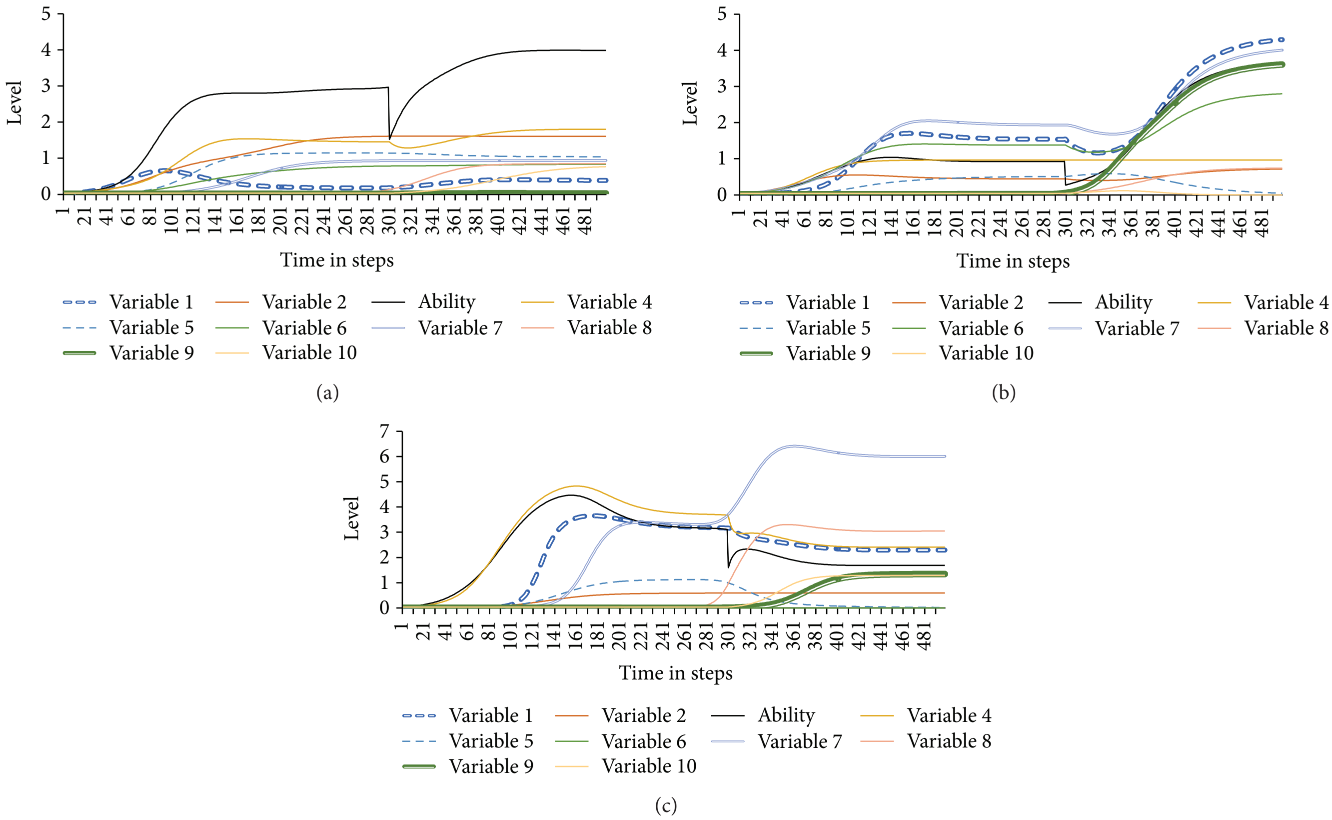

FIGURE 2: Results of the simulations of three athletes' talent networks. The black solid lines in the graphs correspond to the ability variable, represented by node 3 in the network. The other lines reflect the changes in the dynamic network variables that have supportive, competitive, or neutral relationships with the ability. The meaning of these variables differs among individuals and constitutes an individual's idiosyncratic network. The starting values of the parameters were drawn from the distributions as defined in Table 1.

and soccer players corresponded to those used for the individual simulations of Federer, Williams (tennis), Crosby (hockey), and Messi (soccer). For golf, we used the same parameter settings as for tennis. In order to compare the actual distributions with predictions of the dynamic network model, we simulated the accomplishments for the number of athletes that corresponded exactly to the number of athletes in the actual data samples (i.e., 1528 male tennis players, 1274 female tennis players, 1011 male golf players, 1183 female golf players, 6677 hockey players, and 585 soccer players).

3. Results

3.1. Developmental Trajectories of Athletes. In line with the literature on talent development, and with the fact that the extended logistic growth equation typically generates nonlinear developmental patterns, simulations of the dynamic network model revealed different trajectories of talent development for different athletes. Figure 2 displays the simulations of two athletes' networks (graphs a and b) and shows that they reach comparable ability levels in different ways. Note also how the simulated athletes respond differently (yet ultimately adaptively) to the imposed perturbation when transitioning from youth to professional (i.e., step 300), whereas another simulation generated the realistic scenario of an athlete that could not adapt after the transition (graph c).

In order to check whether the model provides predictions that fit with the archival data we collected, we first determined whether the performance accomplishments generated by the model are in agreement with the data of specific athletes. To model these accomplishments, we assumed that athletes may accomplish an achievement (e.g., winning a tournament or scoring a goal) from the moment they transition from youth to professional. The probability that at a particular moment in time an achievement is accomplished is a function of the ability-tenacity model (3) [45].

Our first simulation corresponds to an athlete who reaches an ability level of 20.00, which is 17.74 standard deviations above the mean ability level ($M_{\text{ability}} = 1.36$, SD = 1.27). We connected the ability development of this athlete to a low φ parameter (0.0002) to simulate grand slam victories in tennis, yielding 13 achievements ($M = 14.20$, 95% CI = 6.95 – 21.45 at 1000 simulations with the same ability and tenacity levels). We compared the model prediction with the data of Roger Federer at the time of data collection. We found a good qualitative resemblance in terms of the simulated

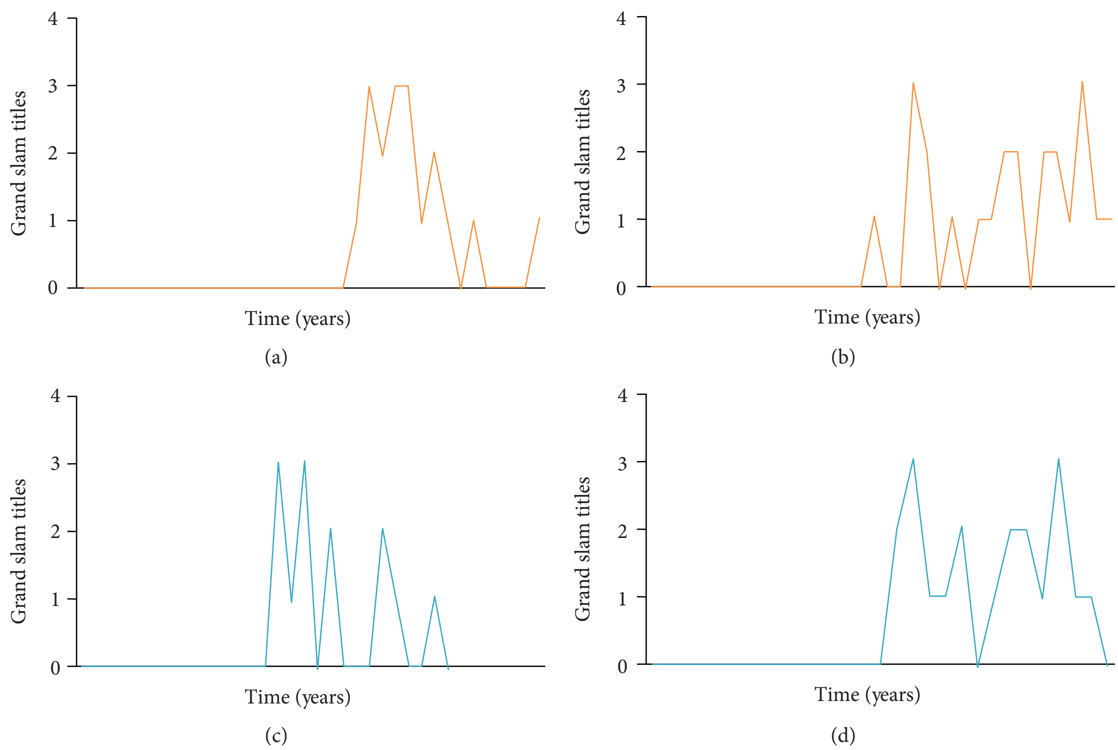

Figure 3: Trajectories of performance accomplishments for Roger Federer and Serena Williams. Graph (a) corresponds with Federer's actual trajectory of grand slam titles per year, and graph (c) with a simulated trajectory; graph (b) corresponds with Williams' actual trajectory of grand slam titles per year, graph (d) with a simulated trajectory. In graphs (c) and (d), one year corresponds to 20 simulation steps.

trajectory (see Figures 3(a) and 3(c)) and the total number of grand slams won (18), which falls within the simulated 95% confidence interval (CI). The second set of graphs corresponds to the Grand Slam titles of Serena Williams according to the actual and simulated data (see Figures 3(b) and 3(d)). The simulated athlete reaches a maximum ability level of 20.00 and is again connected to a low φ parameter (0.0002). The simulation resulted in a total of 20 achievements ($M = 15.59$, 95% CI = 8.16 – 23.02 at 1000 simulations with the same ability and tenacity levels). In reality, Williams had won 23 Grand Slams, which is included in the simulated 95% CI.

To compare the model predictions with hockey, in which athletes' performances could be measured based on the number of goals they scored, we increased the value of the φ parameter to 0.004, and we set the number of achievements that can be produced at each time step equal to 3. Again, we took the archival data of an exceptional player, in this case Sidney Crosby. The simulation led to a maximal ability level of 11.97 (8.39 standard deviations above the mean) and a total of 337 achievements ($M = 352.02$, 95% CI = 321.21 – 382.83 for 1000 simulations with the same ability and tenacity levels). In his career, Crosby has scored 338 goals in the NHL, which falls within the 95% CI of the simulated data, and the dynamic network model reveals a comparable pattern of goals scored over the years (see Figures 4(a) and 4(c)). Finally, for goals scored in soccer, we used the data of FC Barcelona's all-time top goal scorer, Lionel Messi (see Figures 4(b) and 4(d)). The simulation yielded an athlete reaching a maximum ability of 16.99 (12.36 standard deviations above the mean). The simulation was connected to a φ parameter of 0.002 and a maximum number of goals per time point of 3, resulting in a total of 323 achievements ($M = 331.29$, 95% CI = 303.71 – 358.87 for 1000 simulations with the same ability and tenacity levels). In reality, Messi had accumulated a career total of 312 goals in La Liga, which falls within the simulated 95% CI.

3.2. Distributions of Performance Accomplishments. To test whether the distribution of athletes' achievements follows a power law, in which very few athletes accomplish exceptional achievements across sports, gender, and geographical scale, we conducted our analyses on: grand slam titles in tennis for male and female players, major wins in golf for male and female players, goals scored in the National Hockey League (NHL) competition, and goals scored by FC Barcelona players. Then, we simulated these achievements for populations of tennis, golf, hockey, and soccer players.

For all analyses on the archival data, we found patterns close to a power law in the log-log plots for tennis, golf, hockey, and soccer (see Figures 5 and 6). These power laws are evidenced by the linear regression slopes in the log-log plots (see Tables 2 and 3), which provide a strong fit with the collected data ($R^2 = 0.94$ for male tennis, $R^2 = 0.89$ for

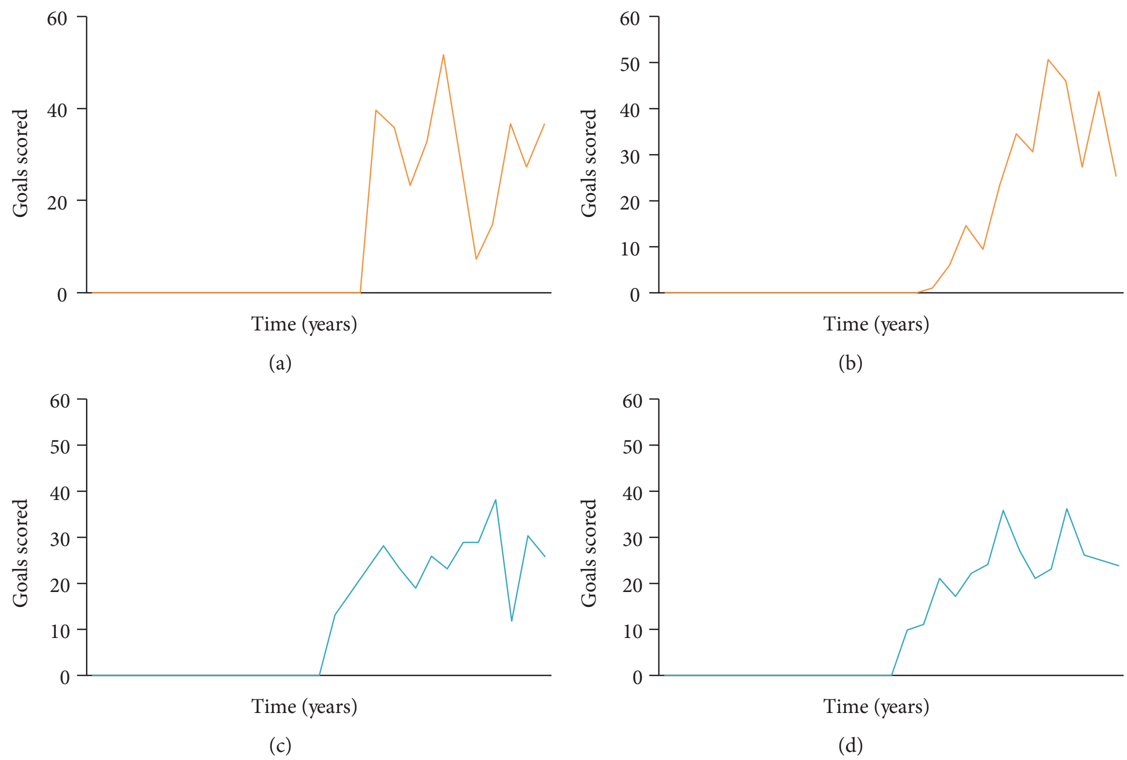

FIGURE 4: Trajectories of performance accomplishments for Sidney Crosby and Lionel Messi. Graph (a) corresponds with Crosby's actual trajectory of goals scored for in the NHL per year, and graph (c) with a simulated trajectory; graph (b) corresponds with Messi's actual trajectory of goals scored for FC Barcelona per year, and graph (d) with a simulated trajectory. In graphs (b) and (d), one year corresponds to 20 simulation steps.

female tennis, $R^2 = 0.99$ for male golf, $R^2 = 0.97$ for female golf, $R^2 = 0.98$ for hockey, and $R^2 = 0.96$ for soccer). The results imply that the extremely skewed distributions hold across sports, gender, and geographical scale.

Simulating the performance accomplishments based on the dynamic network model, we find the same kinds of distributions as in the archival data. This is implied by the results that (i) the simulated number of players with zero accomplishments is close to the actual number of players with zero accomplishments, (ii) the simulated maximum number of accomplishments for an athlete within a given athletic population is close to the actual maximum number of accomplishments by an individual athlete, and (iii) the regression slopes (beta coefficients) of the log-log plots, which provide an estimate of the power parameter, show close resemblances between the simulated and archival data. Table 2 provides an overview of the results for the individual sports, and Figure 5 shows the log-log plots of the athletes' achievements in the individual sports according to the archival and simulated data.

The results for hockey and soccer are shown in Table 3, and Figure 6 displays the log-log plots of the players' achievements (i.e., goals scored) according to the archival and simulated data.

4. Discussion

Here, we proposed a dynamic network model of talent development and tested whether it explains the individual developmental patterns and achievements of elite athletes, as well as the distributions of achievements across populations of athletes in different sports. We therefore (i) defined the model principles based on the definition of talent and the literature on human developmental processes; (ii) ran simulations of the defined dynamic network model; (iii) collected performance attainments of specific cases in tennis (Federer and Williams), hockey (Crosby), and soccer (Messi) and compared their data with the patterns generated by simulations of our dynamic network model; and (iv) collected performance attainments across the population of elite athletes in tennis, golf, hockey, and soccer and compared the population distributions with those generated by the dynamic network model.

Regarding the ability-level trajectories, the dynamic network model generates nonlinear patterns that differ per individual athlete. This is in accordance with previous studies on talent development in sports [19, 35] and the nonergodicity of developmental processes [25, 26]. In order to model the process of talent development, we used a model of change in individuals. In such a model, the associations between the variables over the course of time differ quite fundamentally from statistical associations in a sample of individual cases and cannot be interpreted as random fluctuations around a common pattern present in all individual cases of a particular group (e.g., athletes in a particular sports). In addition, changes in an individual athlete's trajectory are not driven by the nature of some specified variable. For

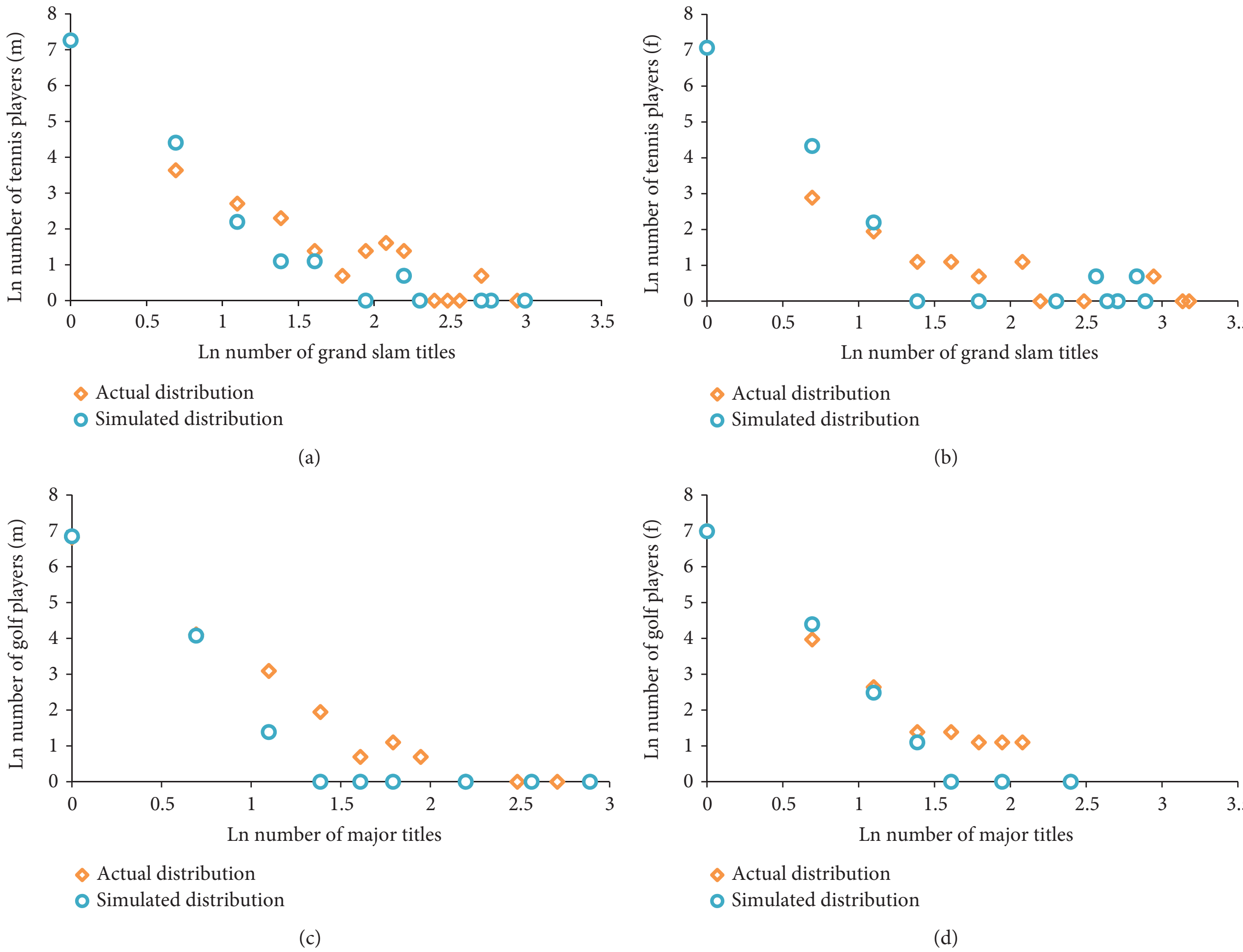

Figure 5: Log-log plots of the number of victories +1 against the number of athletes in the individual sports. The graphs correspond to actual and simulated grand slam titles by male players (a); actual and simulated grand slam titles by female tennis players (b); actual and simulated major titles by male golf players (c); and actual and simulated major titles by female golf players (d). Displayed simulated results are based on one simulation round of the population. For plots showing the raw actual and simulated data, see our research materials at https://hdl.handle.net/10411/ZTS6LQ.

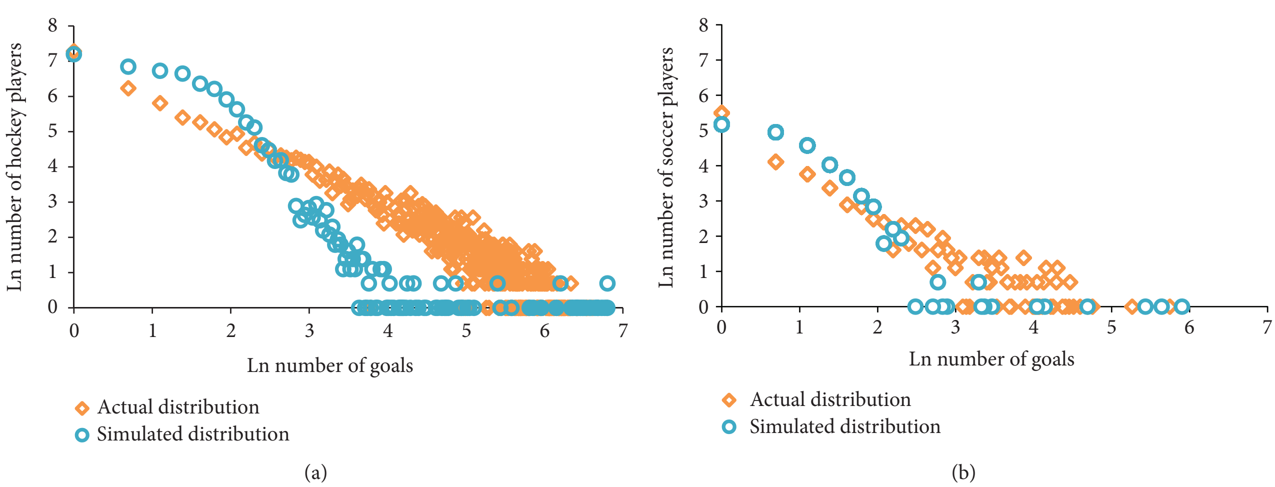

Figure 6: Log-log plots of the number of goals +1 scored against the number of athletes in the team sports. The graphs correspond to actual and simulated goals scored by National Hockey League (NHL) players (a), and actual and simulated goals scored by soccer players from FC Barcelona (b). For plots showing the raw actual and simulated data, see our research materials at https://hdl.handle.net/10411/ZTS6LQ.

Table 2: Achievements in individual sports according to archival and simulated data.

Sport	Measure	Actual titles	Simulated titles
Tennis (m)	Athletes with 0 titles	1439	1417.60 ± 9.38
	Maximum number of titles	18	21.96 ± 7.62
	Beta coefficient (β_1)	−3.32	-3.59 ± 0.21
Tennis (f)	Athletes with 0 titles	1231	1183.10 ± 8.90
	Maximum number of titles	22	20.46 ± 8.99
	Beta coefficient (β_1)	−3.26	-3.58 ± 0.24
Golf (m)	Athletes with 0 titles	911	937.92 ± 8.54
	Maximum number of titles	14	16.40 ± 7.73
	Beta coefficient (β_1)	−3.40	-3.64 ± 0.26
Golf (f)	Athletes with 0 titles	1098	1099.74 ± 16.08
	Maximum number of titles	10	20.62 ± 8.89
	Beta coefficient (β_1)	−3.64	-3.59 ± 0.25

Note. The measures include distributional characteristics of achievements for male (m) and female (f) tennis (grand slam titles), and for male (m) and female (f) golf (major titles). The averages and SDs under the simulated titles are based on 50 simulations of the entire populations.

Table 3: Achievements in team sports according to archival and simulated data.

Sport	Measure	Actual goals	Simulated goals
National Hockey League	Athletes with 0 goals	1456	1327.40 ± 27.99
	Maximum number of goals	894	899.42 ± 2.96
	Beta coefficient (β_1)	−1.08	-1.16 ± 0.01
FC Barcelona	Athletes with 0 goals	244	193.02 ± 10.24
	Maximum number of goals	312	463.68 ± 25.19
	Beta coefficient (β_1)	−1.27	-1.25 ± 0.05

Note. Measures correspond to distributional characteristics of achievements (goals scored) for male athletes in hockey (NHL) and soccer (FC Barcelona). The averages and SDs under the simulated titles are based on 50 simulations of the entire populations.

instance, the reason that an athlete may not adapt to a transition from youth to professional (Figure 2(c)) is not “located” in an underdeveloped variable specifying “ability to adapt,” but rather lies in the structure of the connections between the variables in the athlete’s idiosyncratic network. These findings support the general observation that talent development in sports is a nonlinear process in which nature and nurture are intertwined [9, 10, 27, 36].

However, we also went beyond general description of the trajectories of ability development and connected the dynamic network model to an ability-tenacity product model to examine athletes’ simulated performance attainments. Doing this, we were able to replicate the qualitative pattern of achievements of some exceptional athletes in different sports (i.e., Federer, Williams, Crosby, and Messi). Together, these results indicate that the dynamic network model can explain the individual trajectories of talent development, which would not be possible using traditional linear models, such as regression models applied to samples of athletes [61–63]. Indeed, a recent study attempted to generate the typical properties of excellent performance across domains (e.g., sports, science, and music) by simulating a model based on the standard statistical assumption that abilities are normally distributed across the population and result from additive effects of various relevant performance-related variables. No matter how the parameter values were tweaked, predictions did not come near the patterns found in the observed data across excellent performers [16].

Furthermore, in line with previous research [16, 44, 46–48], we found that athletes’ performance attainments in tennis, golf, hockey, and soccer conform to extremely skewed distributions at population level. This means that the exceptional athletes are in the extreme right tail of the highly skewed distributions and that the great majority of athletes accomplished considerably less. As our results show, a power law holds across sports (tennis, golf, hockey, and soccer), gender (male, female), and geographical scale (worldwide competition in tennis and golf, national competition in hockey, and within one club in soccer). The dynamic network simulations revealed interesting resemblances with the actual data in terms of the overall (power law) shape of the distributions, as well as more specific measures such as the number of professional athletes with zero countable achievements and the maximum number of achievements by one particular athlete in a given sports.

The resemblances between the performance accomplishment distributions based on the archival data and the model predictions were more evident for the individual sports than for the team sports. In particular, the predictions in hockey provided a distribution that was more curved than the actual distribution, although qualitative similarities were still apparent. An interesting question is whether there is any comparably general alternative model of talent development that provides an even better qualitative and quantitative fit with the data in team sports. Regarding the soccer data we collected, one may criticize that we took the goals scored by all Barcelona players rather than only the attacking players. We decided to do so, because it is difficult to draw a line defining which players clearly have (no) attacking tasks on the field. Interestingly, if one would only take only the attackers of FC Barcelona, one would again find a strongly skewed distribution. This supports the claim that distributions of the power-law kind hold across all kinds of scales of analysis (see the research materials at https://hdl.handle.net/10411/ZTS6LQ).

4.1. Theoretical and Applied Implications. A dynamic network model seems to underlie the development of talent in sports, which ultimately results in exceptional achievements for very few athletes. This conclusion has important implications at both a theoretical and practical level. At a theoretical level, an important step is to move away from a focus on unravelling the underlying variables of talent development and to embrace the complex interactions that exist across performer, environment, practice, and training [17, 27, 37]. Exceptional growth of a particular ability in a specific person can be achieved by a wide variety of connection patterns, which is in line with empirical findings showing that the dynamics of talent development is highly idiosyncratic and differs among individuals [7, 9, 27]. Novel challenges in the direction of investigating dynamic talent networks are getting a grip on the variables involved in individual networks, as well as posing network-oriented research questions to be further investigated. The first challenge can be addressed by conducting longitudinal research in which individual patterns of development are accounted for [37, 64]. Different personal and environmental variables that are important to an (youth) athlete's development can be specified and tracked over time. Importantly, a major focus should be on how changes in the variables are embedded in the network and spread their influence. Although such applications do not exist yet in the domain of talent development, important steps are currently made in the domain of clinical psychology [65–67]. For instance, in a recent study on mental health monitoring, researchers collected online diary data from the Dutch population and used autoregressive modelling to detect directed relationships as they exist between variables in *individual* networks [67]. Although the statistical techniques applied were still proceeding from a linear model, this approach is an important first step to capturing individual developmental patterns based on empirical data.

With respect to the point of posing network-oriented research questions, the focus should be on the *structure* and *dynamics* of the network. For instance, what would happen when values of coupling parameters could change as a result of long-term effects of one component on another component? Furthermore, according to recent advances in network sciences, the structure of the network characterizes particular key features, such as resilience [68]. Recent research has made interesting advances in defining a universal resilience function that depends on the dynamics and topology of a network [69]. This may open the door to future studies aimed at examining whether particular talent networks are more or less resilient to perturbations such as youth-to-senior transitions or different setbacks during a career. Understanding the link between network configurations, the development of talent, and overcoming setbacks can be accomplished by combining computer simulations with data from athletes' diaries, for example.

From an applied perspective, talent detection programs in research and practice around the world are still largely based on the assumption that talent can be detected in certain variables "in the individual" and that it can be discovered at an early age [9, 14, 27, 36, 70, 71]. Given the current knowledge on talent development, the archival data we collected, and the patterns simulated by the dynamic network model, one may cast major doubt on this kind of practice. From the dynamic network perspective, various kinds of direct and indirect multiplicative relationships between dynamic variables may exist and lead to different developmental trajectories. Accordingly, a recent study based on computer simulations already showed that, across achievement domains, dynamic network predictions reveal that early detection of later ability levels is virtually impossible [16]. Furthermore, a meta-analytic study recently stated that there is no clear set of variables that can predict career success in sports [72].

5. Conclusions

The dynamic network model provides a comprehensive framework to understand the theoretical principles underlying the development of talent. The model suggests that talent emerges from intra- and interindividual variations in the composition of individual dynamic networks. Having demonstrated that the foundation of the dynamic network model explains empirical observations across a variety of sports, it is now time to explore and test the variety of practical applications of the dynamic network perspective.

Data Availability

The basic dynamic network model, the manual of the model, the archival data, and the simulated data are available at https://hdl.handle.net/10411/ZTS6LQ.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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