

A complex systems view on physical activity with actionable insights for behaviour change

Julia Schüler¹✉, Matti T. J. Heino², Natàlia Balagué³,
Angel M. Chater^{4,5}, Markus Gruber¹, Martina Kanning¹, Daniel Keim⁶,
Daniela Mier⁷, Maria Moreno-Villanueva¹, Fridtjof W. Nussbeck⁷,
Jens Pruessner⁷, Termeh Shafie⁸, Michael Schwenk¹ & Maik Bieleke¹

Physical inactivity and its associated health and economic burdens continue to rise despite decades of interdisciplinary research aimed at promoting physical activity. This Perspective takes a complex systems view on physical activity, proposing that at least two layers of complexity should be considered: (1) interactions between various physiological, psychological, social and environmental systems; and (2) their dynamic interactions across time. To address this complexity, all stages of the research process—from theory and measurement to study design, analysis and interventions—must be aligned with a complex systems perspective. This alignment requires intensive interdisciplinary collaboration and an integration of basic and applied research beyond current research practices to create transdisciplinary solutions. We offer actionable insights that bridge the gap between abstract theoretical approaches (for example, complex systems and attractor landscape frameworks of behaviour change) and practical research on physical activity, thereby laying a foundation for more effective behaviour change interventions.

Physical inactivity is a major public health threat, ranking as the fourth leading cause of mortality¹ and a key risk factor for non-communicable diseases^{2,3} and poor mental health⁴, while also contributing to substantial economic costs⁵. Globally, 31.3% of adults do not meet the physical activity (PA) levels recommended by the World Health Organization^{6,7}. By contrast, the health benefits of PA are well established; it is widely recognized as a core intervention for preventing non-communicable diseases⁸ and mitigating mental health issues^{9,10}. Despite extensive efforts and rigorous standards for developing behaviour change interventions, physical inactivity remains a persistent and growing global issue^{11–13}.

In this Perspective, we argue that advancing PA promotion requires the conceptualization of PA as a complex system^{14,15}. We advocate for aligning all steps in the research process to this complexity. Viewing PA as a complex system means recognizing it as the outcome of dynamic interactions among multiple processes that operate across different timescales (for example, minutes, days and weeks) and hierarchical scales (for example, individual, interpersonal and societal)^{14,16,17}. This includes physiological (for example, neuromuscular, cardiovascular, endocrine and respiratory functions), psychological (for example, motivation, cognition, emotion regulation and social-cognitive

¹Department of Sport Science, University of Konstanz, Constance, Germany. ²Medical Faculty Mannheim, University of Heidelberg, Heidelberg, Germany. ³Complex Systems in Sport Research Group. Institut Nacional d'Educació Física de Catalunya (INEFC), University of Barcelona, Barcelona, Spain. ⁴Centre for Health, Wellbeing and Behaviour Change, Institute for Sport and Physical Activity Research, University of Bedfordshire, Luton, UK. ⁵Centre for Behaviour Change, University College London, London, UK. ⁶Department of Computer Science, University of Konstanz, Constance, Germany. ⁷Department of Psychology, University of Konstanz, Constance, Germany. ⁸Center for Data and Methods, University of Konstanz, Constance, Germany.

✉e-mail: julia.schueler@uni-konstanz.de

constructs), social (for example, social networks and support systems) and environmental processes (for example, infrastructure, urban design and access to resources). Crucially, a complex systems perspective emphasizes that these processes are not merely additive but are characterized by interdependencies, feedback loops, adaptive mechanisms, contextual sensitivity and emergent properties (for example, stable patterns of activity or inactivity) that cannot be fully understood by studying components in isolation. Thus, it is necessary to study temporal dynamics, including fluctuations at different resolutions, critical phase transitions, behaviour adoption and maintenance, and the resulting dynamic interactions (for example, how physical capacity, self-efficacy, social norms and environmental conditions co-influence behaviour dynamically over time). Understanding, predicting and influencing PA therefore requires integrative, interdisciplinary approaches that account for this complexity rather than isolating single variables.

Calls for interdisciplinary approaches in sport science underscore the value of collaborative approaches to studying PA^{18–20}. They receive empirical support from a steadily growing body of literature in which considerations from at least two disciplines are combined. For example, PA can be predicted from interactions between the built environment and social cognition²¹, and the dynamic relationship between psychological and physiological determinants has been shown to explain sports performance²².

While interdisciplinary expertise—in terms of both theoretical grounding and methodological practice—is a necessary foundation, a complex systems perspective offers more than the sum of disciplinary parts. It provides a theoretical and methodological lens through which to specifically investigate how these diverse processes interconnect, influence each other over time and generate the overall behavioural patterns of PA. This focus on dynamic interplay and emergent outcomes is the distinctive contribution of a complexity approach²³ (see the discussion below on layers of complexity).

An additional essential prerequisite is the integration of basic and applied research perspectives. PA research is often divided between two approaches: one focused on understanding behaviour (for example, describing, measuring, explaining and predicting PA) and the other on changing behaviour through interventions. While fields such as behaviour change science and translational behavioural medicine aim to integrate these aspects, research in the PA domain has largely focused on the mechanisms of the implementation of interventions^{24,25}, often with limited attention to how a deeper understanding of PA itself (for example, the interplay of physiological and psychological processes) could inform the development of interventions. We propose that a complex systems approach should integrate both aims—understanding PA and changing PA—throughout the research process.

Figure 1 provides a conceptual summary of the purpose of our Perspective. A complexity perspective on PA demands that we rethink conventional research paradigms and align all components of the research process—including theory, measurement, study design, analysis and intervention—to the complexity inherent to PA. This complexity includes at least two layers: the interactions between multidimensional processes (for example, physiological, psychological, social and environmental) and the temporal dynamics within and across these processes (for example, nonlinear patterns and reciprocal influences). We discuss these two layers of complexity with regard to their implications for all stages of the research process with a focus on actionable insights. We structure this Perspective by considering how to align theoretical approaches, measurement approaches, study designs, analysis approaches and intervention strategies to the complex systems perspective of PA.

Theoretical approaches

In this Perspective, we propose to consider, analyse and promote PA by adding two layers of complexity: interactions across processes and their temporal dynamics.

Interactions across processes

PA involves a complex interplay of physiological, psychological, social and environmental processes. Even the seemingly simple decision to terminate an exercise when it becomes more difficult to perform reflects a complex interplay of muscle fatigue and perceived exertion^{16,26}, alongside beliefs about capability and consequences. This is difficult to reconcile with a reductionist approach in which physiological and psychological systems are studied in separate strands of research. Psychology has excelled in designing PA interventions grounded in psychological parameters (for example, modifying motivation) and has considered complexity within psychological components in several approaches^{27–30}. However, it often neglects physiological factors^{31–33} or addresses them as secondary outcomes³⁴, although better integration is called for³⁵.

By contrast, sport science relates properties of training such as type, frequency and intensity to a wide range of physiological parameters (for example, heart rate, oxygen uptake and muscle glycogen levels), but often without considering psychological, social and environmental parameters³⁶. Current approaches of network physiology of exercise propose that physiological states are products of nested dynamics of vertical (among molecular, cellular, tissue, organ and other levels) and horizontal (at the same organizational level, such as between different organs—for example, muscles, liver, lungs and brain) nonlinear interactions³⁷.

There is a noticeable shift in disciplines towards modelling PA as a complex phenomenon; however, the complexity is still predominantly confined to processes within individual systems (for example, psychological or physiological processes). Recent health promotion approaches view PA more broadly as a multidimensional behaviour of complex processes across different systems: health behaviours and outcomes are the products of dynamic, interrelated factors within the individual (psychological and physiological) and their (social) environments rather than being static or occurring in isolation^{14,38,39}. These approaches propose considering interactions and feedback loops among these processes, enabling a more comprehensive understanding of health phenomena and the development of more adaptive strategies for health promotion^{14,40} (see Fig. 2a for an illustration).

The interconnectedness of these processes is evident in many examples: muscle fatigue experienced at the onset of a new training session can diminish motivation, reducing the willingness to exert further effort^{41,42}, which in turn undermines PA levels and elicits negative emotions. The stagnation of cardiovascular fitness then leads to higher effort costs⁴³, further reducing motivation, fitness and PA. These dynamics can be exacerbated by environmental barriers—such as limited access to green spaces or sports facilities—which reduce opportunities for restorative or enjoyable PA experiences, thereby further amplifying demotivation⁴⁴. Another example is the exercise-induced release of myokines, which affects brain structure and function, enhancing cognitive abilities such as executive functioning⁴⁵. Evidence for the bidirectional relationship between inhibitory control and exercise⁴⁶ suggests that improved self-control fosters exercise adherence, initiating a cycle that spans from molecular interactions to cognitive processes. Figure 2a illustrates the interactions between processes involved in PA.

Temporal dynamics

PA behaviour is not static; it changes dynamically over time⁴⁷. Attractor landscape frameworks, derived from complexity science, provide a conceptual lens for understanding these dynamic aspects of complex systems⁴⁸.

In these frameworks, an individual's current state is symbolized by a ball resting in valleys of varying depth, corresponding to different levels of stability that require more or less energy to change the state⁴⁹. A deep valley represents a relatively stable state, also known as an attractor state⁵⁰. Applied to the field of PA (Fig. 2b), PA-related

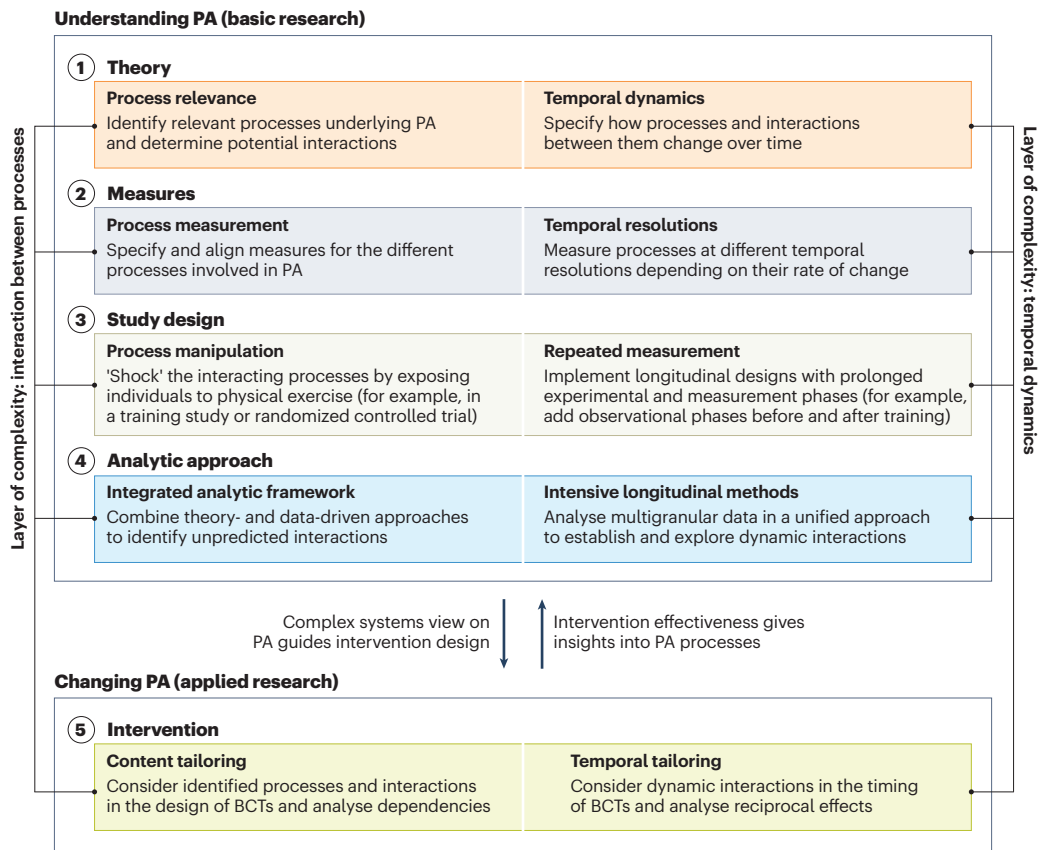


Fig. 1 | Actionable insights for research from a complex systems perspective on PA. How individual research steps can be aligned with the complexity perspective on PA, systematically organized according to the layers of complexity (interactions among psychological, physiological, social and environmental

processes; and temporal dynamics). The numbers correspond to the sections where the alignment of individual research process components with the complex systems approach is discussed.

processes might stabilize in an attractor state as well. An attractor state of physical inactivity, operationalized as not meeting the PA recommendations of the World Health Organization⁶, is shaped by recurrent patterns of interrelated physiological, psychological, social and environmental processes. For example, an individual with low cardiorespiratory fitness, low self-efficacy, limited access to exercise facilities and a predominantly sedentary social network may repeatedly revert to inactivity despite temporary increases in motivation or isolated improvements in a single domain—illustrating how these interacting processes can stabilize each other in an attractor state of inactivity.

Isolated or mild perturbations of the system (for example, a New Year's resolution or an information campaign) might—if at all—cause only temporary back-and-forth oscillations in a deep valley in the landscape, after which the system quickly reverts to its original position at the deepest point in the valley. However, a substantial perturbation or shock has the potential to push the system beyond a critical threshold (tipping point; see, for example, ref. 50; asterisks in Fig. 2b) that can lead to a new attractor state of PA. Such shocks can be observed and assessed in observational studies or, from a more practical research perspective, can be experimentally induced in randomized controlled trials (lightning bolts in Fig. 2c). Potent shocks, such as regular and intense exercise interventions (for example, training studies), are well suited for studying the dynamics of PA. Control theory⁵¹ suggests that stabilizing a system—moving it from an unstable transition state to a stable active state (arrows in Fig. 2b)—requires at least as much energy as was used to cause the initial disturbance.

In the context of PA, it is essential to consider dynamic interactions involved in initiating and sustaining behaviour change. This distinction complements previous research differentiating between behaviour

initiation and maintenance^{52,53} and adds a complex systems perspective based on an interdisciplinary approach. An exemplary research question concerning the dynamic interactions of PA triggered by a training study is: how do self-efficacy and affective responses change with nonlinear improvements in neuromuscular or cardiovascular function from behaviour initiation to maintenance? And how do varying social environments (for example, the activity status of social networks) and physical environments (for example, the availability of sports facilities) modulate their effects on long-term PA? Furthermore, examining interrelations between these processes can help to identify synergies (that is, reciprocal compensations of factors cooperating to achieve a purpose⁵⁴—for example, can high self-efficacy mitigate the need for social support?), which components are indispensable (for example, is physiological training success essential for future PA?) and whether there are PA 'killers' that may inhibit PA maintenance despite favourable developments in other parameters (for example, strong negative affect during training plus urban designs impeditive to PA).

Measurement approaches

Understanding PA as a multidimensional behaviour of complex processes requires data to be collected across multiple systems, contexts and timescales. Commonly used data collection methods limit the extent to which these complex dynamics can be captured¹⁷. Psychological processes, for instance, fluctuate at various resolutions, ranging from very slow changes (for example, in intentions), through often faster fluctuations in mood, to relatively quick changes in emotions and activation. This makes infrequent assessments (for example, designs with pre- and post-assessments) insufficient for accurate characterization.

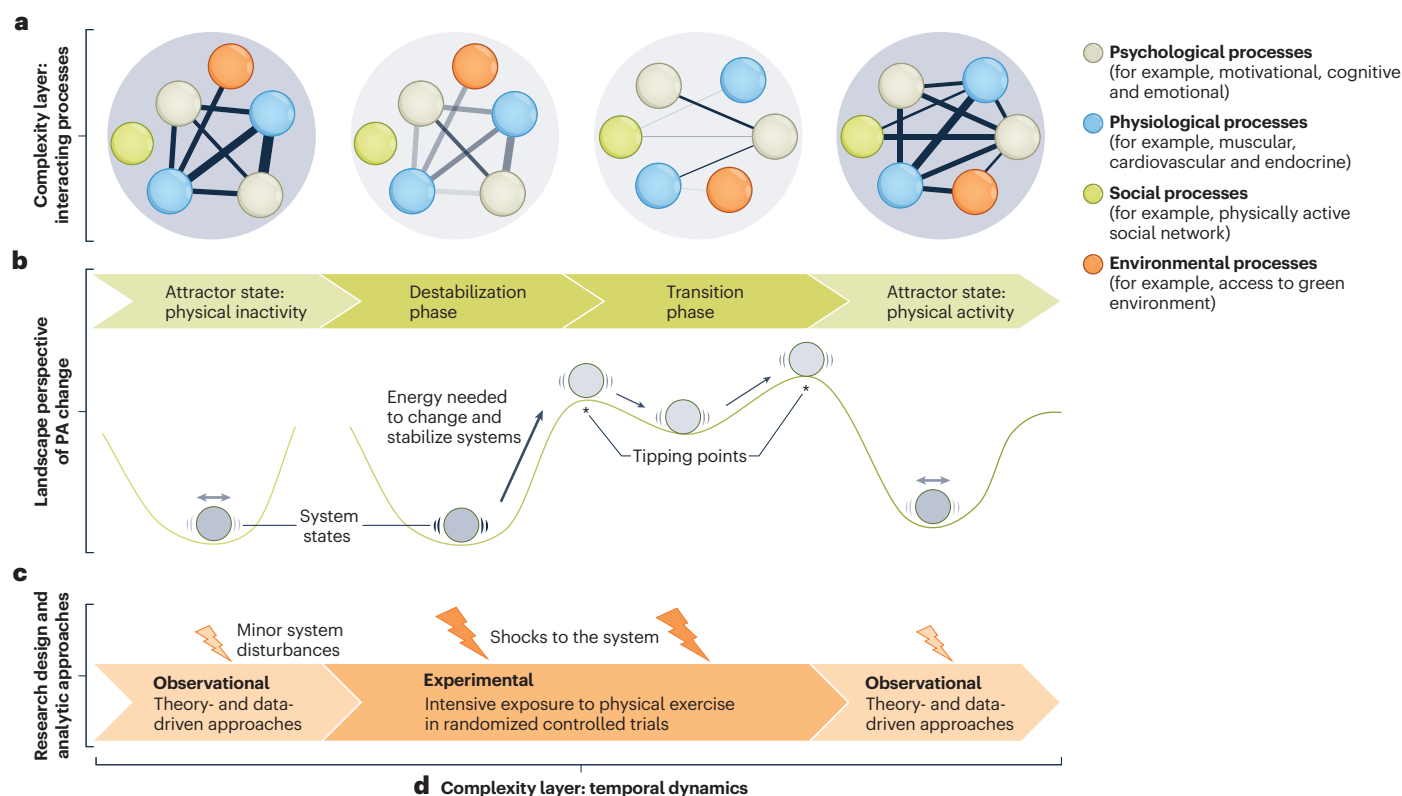


Fig. 2 | Research design capturing dynamic interactive processes related to PA and behaviour change. **a**, Illustration of PA as a multidimensional behaviour of complex interacting psychological, physiological, social and environmental processes. The number, types and strengths of relationships and interactions (connection lines between subsystems) can vary, partly owing to minor disturbances (for example, an information campaign about the benefits of PA) or major disturbances (shocks to the system). A shock to the system can be, for example, intensive exposure to regular exercise provided in a training study. **b**, A landscape perspective illustrating an ideal course of the temporal dynamics

from an attractor state of inactivity to an attractor state of activity, passing through phases of destabilization and transition. **c**, A multi-step research design consisting of observational and experimental phases enables investigators to examine processes of PA and their interactive dynamics. Advanced theory- and data-driven analysis approaches are needed to account for the diversity of data. The illustration is reminiscent of similar representations of attractor landscapes⁴⁸, such as those used in psychotherapy research³⁰. **d**, In all panels, the progression from left to right represents the second layer of complexity: the temporal dynamics inherent in the interactions between processes.

Recent years have therefore seen a surge in dynamic measurement and modelling approaches in behaviour change and PA research⁵⁵, known collectively as intensive longitudinal methods⁵⁶. These methods are research designs that involve frequent, repeated measurements at short resolutions (minutes, hours or days) but over a potentially long time span (weeks, months or years). They are used to capture dynamic processes as they unfold in real-world contexts, allowing the modelling of within-person change and variability over time⁵⁶. Examples include the experience sampling method (prompted reports at random or scheduled times, such as asking participants to report their current mood or activity), ecological momentary assessment (real-time data via mobile devices on behaviours, contexts or physiological states, such as reporting stress levels or social interactions in the moment) and sensor-based monitoring (continuous collection via wearables, such as sport watches or smartphones, of data on activity, location or physiology—allowing us to record, measure such as breathing, VO₂ max, heart rate, motivation or step count)^{57–59}. For example, intensive longitudinal methods have been applied to elucidate the reciprocal relationships between PA and affect^{55,60}, PA and sleep⁶¹, and PA and fatigue⁶². In summary, intensive longitudinal methods are promising to effectively capture the interactive dynamics of processes occurring in PA.

Study designs

To track how interconnected processes transition from an initial state of physical inactivity through phases of destabilization to eventual stabilization in a state of PA—according to the landscape framework

(Fig. 2b)—research can either observe and measure naturally occurring interactive dynamics or combine intensive longitudinal designs with randomized controlled trials in which a system change is artificially triggered through an intervention. This can be done, for example, through intensive exercise training interventions, as commonly used in sport science⁶³. Regularly exposing inactive individuals to exercise in the context of a supervised training study would disturb (‘shock’) the systems and may lead to observable changes in attractor states (Fig. 2b). According to the landscape framework, this should trigger changes in physiological (for example, cardiovascular, neuromuscular, endocrine and sensorimotor), psychological (for example, motivational and emotional), social (for example, social support and networks of physically active individuals) and environmental subsystems (for example, access to sports equipment or training plans) and their interactions. Over time, this exposure should move individuals from an initial state of physical inactivity towards a desired state of activity. Maintaining the system in an active state for a certain period (for example, weeks or months) followed by an observational phase allows researchers to investigate the stability of this new state and the conditions under which the systems might revert to their initial state. This research approach enables the analysis of the interactive dynamics of the systems in both stabilized and destabilized states, capturing the characteristics of PA more comprehensively.

In summary, we propose combining experimental and observational approaches, as shown in Fig. 2c, as the best study design to investigate the complex system of PA. Dynamic interactions that are

beneficial or harmful for a successful transition into a stable state of PA can be identified⁶⁴, and the insights gained can be used to develop effective and scalable interventions outside the laboratory. The suggested study design aligns with the growing body of literature that values the internal validity of randomized controlled trials and the rich data from observational studies, and it suggests using causal inference methods to integrate both⁶⁵.

While fully capturing all processes and interactions in complex systems remains an unattainable ideal—owing to the sheer number of involved processes, their dynamic, nonlinear and context-dependent nature, and limitations of measurement and analysis tools—we recommend that researchers focus on central constructs that are theoretically and empirically linked across system boundaries. Wearable devices offer a feasible approach by automatically collecting physiological (for example, cardiovascular) and environmental (for example, location) data in everyday life. This automation reduces participant burden by enabling continuous, passive data collection⁶⁶. Additionally, wearables can support the assessment of psychological (for example, self-reported affect) and social (for example, the number of friends being around) data in everyday life. By contrast, other measures—such as neuropsychological parameters—are more resource-intensive to collect, typically require laboratory settings and often suffer from limited ecological validity. Nevertheless, they remain indispensable for a comprehensive understanding of PA. Their integration necessitates specific study designs and analysis tools for multigranular data.

Analysis approaches

Integrating theory- and data-driven approaches

Combining experimental and observational approaches enables the investigation of presumed causal reciprocal links between theoretically plausible short-term (for example, fluctuations in affective experience during training) and long-term processes (for example, training-induced increases in cardiovascular and muscular fitness). Interdisciplinary hypotheses about these causal links can be formulated on the basis of existing conceptual and empirical disciplinary work. For example, conceptual approaches to high-intensity interval training in sport science provide guidelines for designing short bouts of exercise to rapidly enhance cardiovascular fitness⁶⁷. However, high-intensity interval training can elicit more negative affective responses such as anxiety, fatigue and total mood disturbance than low-to-moderate-intensity training^{68,69}, and sport psychology has identified these responses as important barriers to exercise adherence and fitness gains⁷⁰. By contrast, self-paced low-to-moderate-intensity training may lack immediate results but fosters gradual fitness improvement by reducing negative affect⁷¹. Additionally, personalized exercise prescriptions enhance self-efficacy⁷², which contributes to improved fitness levels. Higher fitness, in turn, leads to more positive experiences during exercise, such as enjoyment and pleasure, thereby encouraging adherence⁷³.

The strength of theory-driven approaches lies in their ability to simplify complex phenomena, guide the operationalization of concepts and test hypotheses, thereby facilitating scientific progress^{28,31}. However, these very strengths can also limit the range of research questions and the scope of possible answers, potentially restricting researchers from capturing the complexity of phenomena⁷⁴. For instance, contemporary behaviour change theories often depict relationships between variables statically³¹, neglecting the temporal dynamics inherent in PA⁷⁵. This static perspective fails to address critical questions regarding when behavioural changes occur or how predictors vary in their effects during different, possibly idiosyncratic, phases of PA—a phenomenon known as non-stationarity^{15,23}.

Data-driven approaches⁷⁶ do not rely on strong theoretical assumptions and may thus complement theory-driven approaches to uncover patterns and relationships as well as changes of patterns and relationships within the data. Hence, data-driven approaches can

help researchers develop novel hypotheses and advance theory⁷⁷. By integrating theory-driven models with data-driven methods, researchers can leverage the strengths of both approaches to more effectively address the complex, dynamic nature of PA. For example, a theory might suggest that motivation, social support and cardiovascular fitness influence each other over time. These hypotheses can guide which variables to focus on initially. Machine learning methods can add important but unconsidered variables from vast amounts of data, probe their relation with hypothesized variables and condense both into superordinate clusters and dimensions.

Advanced analytic tools

Capturing the interactive dynamics of processes, as also conceptually proposed by behaviour change interventions such as the Behaviour Change Wheel⁷⁸, necessitates advanced methods for analysing intensive longitudinal data⁵⁵. To test theoretical hypotheses about these dynamics, sophisticated techniques such as multilevel dynamic structural equation modelling^{79–81} or continuous time structural equation models⁸², as well as a combination of the two⁸³, are available. Moreover, using a network perspective allows the application of agent-based models such as stochastic oriented models⁸⁴. For example, questions such as “Are affective states linked with PA in unidirectional or reciprocal ways? How does this relationship change over time with altering physiological parameters (for example, fitness and muscle strength) and varying training parameters (for example, intensity and frequency)? Do traits such as dispositional self-control and perception of effort moderate these relationships?” can be examined using one of these advanced methods. Furthermore, configurational analysis approaches have recently been highlighted as prime candidates for methods that align with intertwined causal structures common in complex systems⁸⁵. For example, coincidence analysis has been used in implementation science and could examine the combination of self-enacted behaviour change techniques (BCTs) and physiological factors, which enable long-term behaviour change⁸⁶.

However, complex behaviours such as PA involve many processes that are not represented and linked in existing theory. Although, in principle, many variables can be integrated exploratorily in the above-mentioned analysis techniques, it is often not straightforward to do so as it is unclear which variables should be integrated as covariates, moderators or mediators, for example. This lack of knowledge necessitates complementary exploratory approaches to generate new hypotheses based on diverse data sources. Machine learning, for instance, is a powerful data-driven tool that can deal with large datasets, including those that encompass data from physiological, psychological and external systems, to identify predictors of PA and exercise behaviour and to assess treatment responses⁸⁷. Techniques such as network analysis²⁷ and recurrence network analysis⁸⁸ enable researchers to explore complex relationships between various psychological and physiological parameters related to PA and represent them in parsimonious networks. Moreover, relational data provide an additional dimension in the analysis: do people with specific levels of PA influence each other, and if so, are these behavioural changes contingent on other psychological and physiological variables? This allows the identification of features such as key nodes—specific behaviours or specific physiological factors, for example—that may influence overall activity levels or adherence to exercise programmes. Visual analytics⁸⁹, which involves the interactive exploration and analysis of data through visual representations such as interactive charts and dashboards, helps researchers to gain insights into patterns, trends and relationships within PA data. These insights can then inform machine learning, advanced network modelling (such as stochastic actor-oriented models) and other hypothesis testing approaches. In sum, advanced methods in exploratory approaches in addition to theory-driven approaches provide a deeper understanding of PA dynamics, which is necessary to guide the development of intervention strategies.

Intervention strategies

Benefits of considering dynamic interactions for BCTs

Decades of innovative and rigorous scientific work⁹⁰, including the development of theory-derived BCTs^{91,92} and the use of robust methodologies such as randomized controlled trials^{12,93} and large sample sizes (for example, mega studies⁹⁴), have generated a multitude of BCTs with effects on PA behaviour of an average small to medium effect size ($d = 0.21$)⁹⁵. Yet, this effect size is equivalent to an increase of 1,320 steps per day or 15.6 additional minutes of daily moderate to vigorous PA. In this Perspective, we propose that traditional tailoring of BCTs—based on factors such as participants' age, sex, preferences or culture^{96,97}—should be complemented by tailoring that considers the layers of complexity within PA, including interactions between processes and their temporal dynamics. Understanding complex interactions among muscular, affective and motivational factors, for example, can aid in selecting effective BCTs at the right time. PA requires effort, which can hinder adherence owing to its aversive nature, leading to fatigue and decreased motivation and ultimately disadvantaging muscle strength development. To break this cycle, individuals can learn to ascribe value to effort^{98,99}—for example, by introducing role models who value effort¹⁰⁰. It is also important to consider reverse causality, as changes in muscle strength can alter perceptions of effort. Providing encouraging feedback on strength improvements can help individuals to view their efforts as more controllable and worthwhile.

Gained insights into the temporal dynamics of processes involved in PA can enrich and help to further develop established approaches that already consider temporal tailoring (Fig. 1). Approaches to temporal tailoring of BCTs, which have so far distinguished between adoption and maintenance phases^{101,102}, can be further differentiated along the time axis, considering recursive and nonlinear relationships and incorporating additional physiological and psychological parameters. For example, certain BCTs might be most effective during the adoption phase of exercise because they help to destabilize the initial attractor state of physical inactivity (for example, offering monetary incentives, creating strong plans or providing regular guidance and feedback). According to our landscape framework (Fig. 2b), substantial energy is required to destabilize this stable state of inactivity, which may demand particularly strong or combined BCTs. These interventions might be effective only if other interacting systems contribute supportively (for example, increasing physical fitness, reducing aversion, minimal muscle pain and strong cortisol release). Other BCTs might be more effective during the maintenance phase by stabilizing a new, active state (for example, fostering the anticipation of positive experiences and self-monitoring), which in turn might vary with muscle gain or perception of fatigue. Another example of temporal tailoring is that BCTs should be administered when they are likely to exert the greatest influence on a particular individual, such as providing social support in moments of low social encouragement (for example, when alone or surrounded by inactive peers) or offering timely feedback to mitigate anticipated setbacks (for example, muscle soreness following a workout). This can provide valuable insights for just-in-time interventions¹⁰³. A complex systems understanding, particularly of an individual's current state within their attractor landscape and their sensitivity to perturbation, can provide a stronger theoretical basis for when and how to deploy just-in-time interventions effectively. Additionally, the effectiveness of BCTs should be assessed at times when changes in outcomes can be realistically expected, according to the timescales of individual psychological and physiological processes. In summary, detailed knowledge of the dynamic interactions between the psychological, physiological, social and environmental processes involved in PA can greatly contribute to research on the effectiveness of BCTs¹⁰⁴ by aligning the administration and evaluation of BCTs with the interactive and temporal characteristics of PA.

While temporally tailoring BCTs to interactive dynamics remains methodologically challenging—particularly outside controlled

settings—emerging tools such as ecological momentary assessments¹⁰⁵ and individual just-in-time adaptive interventions^{106,107} offer promising ways to detect relevant states and deliver BCTs at appropriate times. Nowadays, wearable technologies can, for example, detect serious falls with built-in accelerometric sensors, alert us to arrhythmias of the heart using heart rate monitors, rate the quality of our sleep and recovery with algorithms, connect us with others via interactive training and activity apps, monitor our well-being via self-assessment ratings and predict the spread of diseases on the basis of the spatial and temporal proximity of other devices¹⁰⁸. Though still evolving and currently capturing the complexity of PA only to a limited extent, these developments tap into many of the psychological, physiological, social and environmental individual processes we have referred to in this Perspective.

Dynamic BCTs as parts of complex systems

Furthermore, from a complex systems perspective, the role of BCTs might need to be reconsidered. Recent research has started to interpret behaviour change mechanisms through the lens of complex systems, using advanced research methods and analyses¹⁵. Rather than considering BCTs solely as external triggers for complex changes, these approaches consider that people self-enact BCTs as self-regulatory tools (for example, engaging in planning and self-monitoring on their own^{109–111}). It is plausible that changes in behaviour or physical fitness (or other changes in subsystems) prompt people to adjust their BCTs or alter them depending on their perceived effectiveness, which in turn makes BCTs an integrated part of an interactive dynamic in complex systems.

Conclusion

We advocate that aligning all stages of the research process—from theory to intervention—with a complex systems perspective is crucial for developing more effective PA behaviour change strategies. Specifically, this means tailoring these stages to the defining characteristics of PA as taking place in a complex system: (1) the dynamic interactions between physiological, psychological, social and environmental processes; and (2) their evolution over time^{14,37}. We propose to implement study designs that disrupt or shock the involved processes and observe the results, facilitating an examination of the transition from an attractor state of inactivity to one of activity. Addressing these complex dynamics necessitates enhanced interdisciplinary collaboration, involving sports scientists, psychologists, data analysts, sociologists, and urban and landscape environmental planners, alongside professionals from related disciplines such as psychotherapy and biology. By advancing the integration of theories from these disciplines (as illustrated by attempts within sport science¹¹²) and using state-of-the-art exploratory methods, existing theoretical approaches to BCTs can be substantially expanded. This promises new insights into what we have not yet discovered, understood and integrated into existing theories about the complexity of PA.

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Competing interests

The authors declare no competing interests.

Additional information

Correspondence should be addressed to Julia Schüler.