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Attractor landscapes: a unifying conceptual model for understanding behaviour change across scales of observation

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ABSTRACT
Models and theories in behaviour change science are not in short supply, but they almost exclusively pertain to a particular facet of behaviour, such as automaticity or reasoned action, or to a single scale of observation such as individuals or communities. We present a highly generalisable conceptual model which is widely used in complex systems research from biology to physics, in an accessible form to behavioural scientists. The proposed model of attractor landscapes can be used to understand human behaviour change on different levels, from individuals to dyads, groups and societies. We use the model as a tool to present neglected ideas in contemporary behaviour change science, such as hysteresis and nonlinearity. The model of attractor landscapes can deepen understanding of well-known features of behaviour change (research), including short-livedness of intervention effects, problematicity of focusing on behavioural initiation while neglecting behavioural maintenance, continuum and stage models of behaviour change understood within a single accommodating framework, and the concept of resilience. We also demonstrate potential methods of analysis and outline avenues for future research.

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Attractor landscape; complexity; complex systems; behaviour change; dynamics

Introduction

Behaviour change science is concerned with investigating the initiation and maintenance of a vast array of behaviours (Hagger, Cameron, et al., 2020). An ultimate goal is to use theory and evidence to understand change, and then develop effective interventions to achieve desired behavioural outcomes in ecologically valid contexts, i.e., the 'real world'. Accordingly, there are many different models, frameworks and theories to choose from, when one is tackling problems where behaviours are key components, ranging from lifestyle diseases to climate change and pandemics. Indeed, behaviour change theories are so abundant (Michie, West, et al., 2014), that an outsider might be justified to ask, whether there is one (or several) for every conceivable problem – which is not wholly unreasonable, as the context of behaviour change has been widely acknowledged to be a key feature of the behavioural challenge at hand (Craig et al., 2018; Skivington et al., 2021). Moreover, it is widely agreed that in behaviour change intervention development, theoretical eclecticism is important: diverse approaches can complement each other, offering different perspectives to

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what needs to be accounted for, in order to start untangling the problem at hand (Bartholomew Eldredge et al., 2016). Still, we would like to argue that there remain hitherto untapped transdisciplinary perspectives, which have the potential to advance the science and practice of behaviour change.

The first avenue to interpret the current state-of-the-art lies in the paradigm which proceeds via a process of atomising: In spite of its theoretical eclecticism, behaviour change science has thus far mostly operated via a process of breaking things down. For example, the widely used Behaviour Change Wheel (Michie, Atkins, et al., 2014; Michie et al., 2011) and Intervention Mapping (Bartholomew Eldredge et al., 2016) frameworks advise that societal challenges are broken down into (leverageable) *behaviours* to be addressed, which consist of smaller elements (dubbed 'sub-behaviours'), performed by individuals. The sub-behaviours can then be broken down into leverageable factors which influence them ('determinants'), categorised under labels such as capability, opportunity and motivation – which can again be broken down into physical or psychological capability, social or physical opportunity, and automatic or reflective motivation (Michie et al., 2011). Similarly, interventions to change these upstream causes of behaviour are broken down into behaviour change techniques or methods, also called 'active ingredients' of the intervention(s) (Kok et al., 2016; Michie et al., 2013). This strategy of proceeding-by-breaking-down entails a reductionist paradigm, which refers to the scientific framework of analysing and describing phenomena in terms of their constituent parts (Kricheldorf, 2016, p. 63). Reductions can be very reasonable and practical, when they point to concrete and intuitively understandable intervention targets and provide a common language to understand intervention content. What easily gets lost in the process, though, is their interactions: If behaviours and their determinants are interdependent, and if interdependencies are key drivers of societal challenges of primary interest, interventions neglecting their dynamic and systemic interplay can lead to omitting crucial facets of the problem's reality (Heino et al., 2021). On some level, many existing frameworks guide the intervention developer to consider interconnections of behaviours and networks of actors, but in the intervention development itself, the potential of these systems has so far been underused.

Secondly, while social ecological models (e.g., Salmon et al., 2020) have attempted to make headway towards a more holistic understanding, behaviour change science usually considers each level of observation to entail its own features and frameworks. For instance, frameworks to understand community behaviour change (e.g., Trickett et al., 2020) differ from those pertaining to dyads (e.g., Scholz et al., 2020), which again differ from those pertaining to individuals.

Thirdly, the field suffers from an overuse of simplistic statistical models for evaluating behaviour change processes, which is likely to distort our thinking of the problem. Behaviour change theories can stem from practical experience (amidst complexity, having been successful in considering the relevant aspects of the problems at hand), and take a qualitatively dynamical view of the change process. Regardless, our field has largely reduced the complex theories into assumption-heavy quantitative empirical models, often in the form of linear regression and structural equation models. This is due to the lack of corresponding methodological tools, which have mostly been developed over the last decades. Many currently used linear models are, indeed, suboptimal for studying phenomena commonly observed in so-called complex systems (Hooker, 2011), where relationships between variables can shift in time and depend on threshold effects. Alternatives such as agent-based modelling (Gomersall, 2018; Nowak & Vallacher, 2019) and recurrence-based approaches (Heino et al., 2021) have been suggested to capture sudden and non-linear change processes (see e.g., Figure 1), but the uptake has been slow.

Currently, reforms linked to the crisis of confidence in psychological research (Nosek et al., 2022) are driving some researchers in the field, to examine how complexity is related to (non-)replicability (Wallot & Kelty-Stephen, 2017). Given that basic assumptions underlying mainstream behaviour change science are in many applications at odds with the nature of the systems under study, researchers should widen their epistemological and ontological perspectives (Heino et al., 2021). In the physical sciences, the reductionist approach has been successful in relatively simple problems,

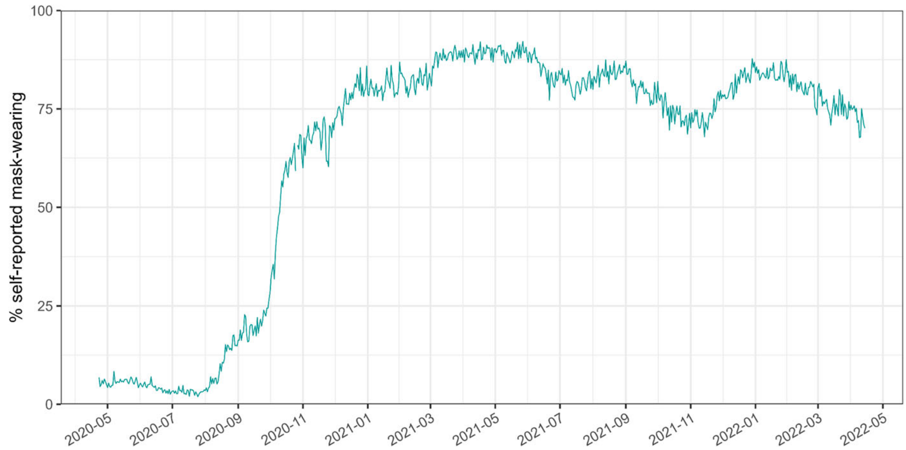

Figure 1. Non-linear social change regarding mask wearing in Finland during the COVID-19 pandemic. In particular, the rapid shift from baseline values to greater uptakes, followed by oscillations, would not be described by linear or even piecewise linear regression. (Data source: Fan et al., 2020).

until the necessity of complementing it with more holistic perspectives became apparent. This process started in the early twentieth century, after scientists realised the impossibility of fully predicting multi-body trajectories (e.g., three or more planets orbiting each other), and re-focused their research questions on studying systemic dynamical features such as *stability*, as well as *organisational principles* of the system (Érdi et al., 2008). The general approach – of complex dynamical systems – has been applied in a wide variety of seemingly disconnected disciplinary fields, from studying galactical patterns that emerge from the interactions of multiple stars (Antoniadou & Libert, 2019), to understanding flocks behaving as collectives, while the trajectory of any particular bird remains impossible to follow (Feder, 2007).

After gaining traction in natural and life sciences, the approach made its way to social sciences and public health (Guastello et al., 2008; Vallacher et al., 2017; Vallacher & Nowak, 2008; Williams & Hummelbrunner, 2011), as well as in a wide variety of other scientific disciplines such as biology and engineering (Bar-Yam, 1997). It has transdisciplinary appeal: for instance, complex dynamical systems approaches characterise the whole of IPCC work, including how both climate change and societal actions to tackle it are presented (Intergovernmental Panel on Climate Change (IPCC), 2022). Recently, uptake of complexity ideas in behavioural sciences has been accelerating (e.g., Marchand et al., 2020); reasons include approachable methodological tools (e.g., Hasselman, 2020), as well as new theorising. Examples of the latter are e.g., the complexity theory of psychopathology (Olthof, Hasselman, Maatman, et al., 2020), the network theory of mental disorders (Borsboom, 2017), the paradigm of 'quantum' behaviour change (Chen & Chen, 2019), and the attitudinal entropy framework (Dalege et al., 2018). A further important influence has been the acknowledgment of important limitations in traditional large sample research, leading to calls for an 'idiographic' approach to psychology (Fisher et al., 2018; Molenaar, 2007). N-of-1 type of designs have been recognised as necessary for such investigations in the area of behaviour change (Kwasnicka et al., 2019), but have thus far not been able to account for e.g., individuals' idiosyncratic embeddedness in time (Bolger & Zee, 2019). In health psychology, sudden shifts between states have been acknowledged in stage theories of behaviour change. These stage theories can, though, be criticised for emphasising universal stages, which could be known a priori (e.g., proceeding from pre-contemplation to contemplation, and onwards to preparation, action and maintenance), instead of being empirically identified, and possibly different for each idiographic behaviour change process (for some criticisms, see e.g., Sutton, 2000, 2005). Recent discussions of novel methods to study complex dynamics in the behaviour change field (e.g., Ruissen et al., 2021) remain confined to extensions of traditional linear models, without delving into e.g., non-linear dynamics, an essential feature of complex systems (Chevance et al., 2021; Heino et al., 2021; also note that e.g., Pearson correlation is a measure of linear dependence only, Sugihara et al., 2012).

It is somewhat lamentable, how little progress has been made in behaviour change science, to complement traditional paradigms with more current ones, despite long-standing calls to do so (Resnicow & Vaughan, 2006). In what follows, we contribute to these calls by introducing the conceptual model of attractor landscapes, based on complex dynamical systems, and describing how it can provide a useful backdrop for understanding behaviour change issues from relapses or successful maintenance of behaviours, to habits and their effects on behavioural stability – in individuals, groups and societies.

Human behaviour change conceptualised as dynamically shifting landscapes

A way to analyse behaviour change from the perspective of complex systems is by the space of the system's possible states – 'state space' – which contains all the potential values of variables of a given system. Here, we use the term *system* generally: for behaviour change researchers, the system of interest is usually an individual, a dyad or a group such as a community. Considering an individual person, every factor of their psychosocial makeup can be considered as a dimension in this state space. Contextual factors, or anything quantifying the relationship between variables, is considered a parameter further moulding the landscape. For practical reasons, we usually limit the variables to a theoretically guided set of what we consider the most important ones.

Importantly, due to non-linearities and inter-relationships, the system does not necessarily visit all possible states with equal probability, but it is often drawn – or *attracted* – towards particular areas of the space of possibilities. The set of values towards which the system tends to evolve and reside is called an 'attractor'. An attractor is a stable region in the total space of possibilities, which the system is comparatively less likely to leave. It should be stressed that this represents a key difference compared to conventional 'ergodic' (Heino et al., 2021; Molenaar, 2008) approaches, which treat every state as equally plausible – in other words, the linear terrain is flat. Attractors are well formalised mathematically in physical disciplines of stochastic dynamical systems (Berglund & Gentz, 2006) and provide an immediate way to bridge quantitative studies and intuition. In fact, their properties can be fully characterised if validated mathematical models are available, but they can be immediately understood as conceptual models with several key features, which we showcase below.

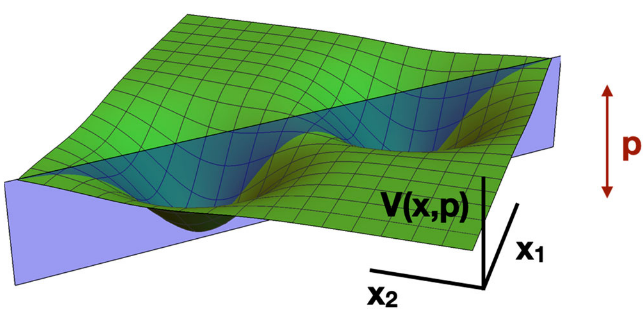

Figure 2. A conceptual basis to draw interpretations and stimulate multidisciplinary modelling. Configurations of variables (x_1, x_2 …) forming the system define its state space. In complex systems, this is often not flat (where every value is equally probable) but displays several equilibria, which depend on the value of extra parameters. Altogether, variables and parameters shape the state space V(x,p), which contains all equilibria. Parameters (p) here quantify the inter-relationships between variables, i.e., 'how much' a variable influences another. Stable equilibria – also known as attractors – are shown as valleys. To investigate how a system goes from one equilibrium to another, it is often sufficient to consider low-dimensional combinations of its variables (Kuehn et al., 2021) (extracted e.g., via principal component analysis, in which case the x_1 and x_2 would represent the two largest principal components, while the blue ridge identifies the main direction of change).

1. Behavioural state as valley. For many real-world systems, attractors can be aptly represented as valleys in a landscape, within a state space. Figure 2 provides an example of a state space with two attractors. In behaviour change theory, we propose that the valleys would be identified by all possible influences on behaviour (or 'determinants of behaviour'). Multiple behavioural states are possible to the extent that different configurations of determinants allow, attract, or repel them. For example, in one attractor (valley), a person would be in a 'mostly taking precautions' state, characterised by mask wearing, physical distancing and air hygiene precautions. The other could represent a state where the person takes few or no precautions. Associating quantitative valleys with qualitative states is an active area of research and of model validation, which would require suitable tools as discussed in later sections of this manuscript, as well as in the technical appendix (https://heinonmatti.github.io/attractor-manuscript/).

It should be noted that context factors, such as immediate environmental demands, intervention opportunities, etc. shape the attractor landscape of possible behaviour states. These are control parameters to shape the potential landscape.

2. Behaviour change as movement between attractors (valleys). In the visual representation, the extent of an attractor's 'pull' is commonly presented as the depth of a valley, and the system's current state can be represented by the location of a ball which resides in the attractor landscape. This is illustrated in Figure 3, where the system shifts from one state to the next.

3. Behavioural influences moulding the landscape's hills and valleys. Valleys can be 'pulled' deeper due to a number of issues in the person's psychological, social and environmental circumstances – for example, a person's system is attracted to the 'performs safety measures' state in a social environment with strong supportive norms. One could think of barriers and facilitators of change for each person as shaping the depth of these valleys and thereby affecting the ease or difficulty of transitioning to the desired state for that person. For example, think of the different factors represented by the Theoretical Domains Framework, a popular integrative framework of influences on behaviour (Cane et al., 2012): various domains from the capability, motivation and opportunities categories may be factors that pull each attractor state deeper, or are responsible for pushing these further up, making the system more conducive to state change (i.e., unstable, with shallow valleys).

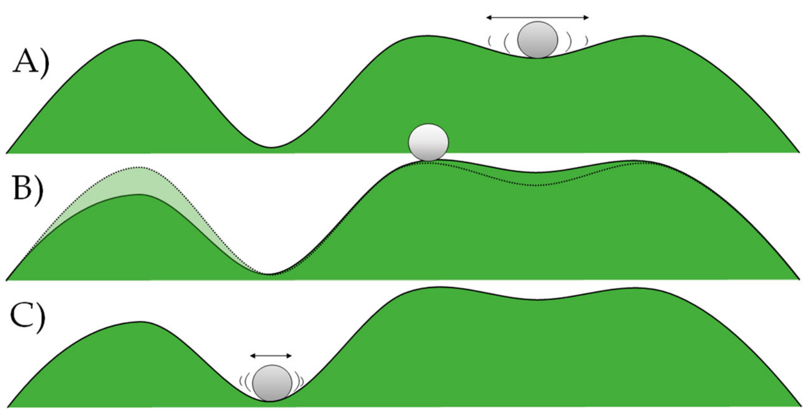

Figure 3. An attractor landscape with three different exemplifying states. Imagine the ball resembling the state of a person – e.g., location of ball in Panel A: 'always takes precautions to mitigate contagion', Panel B: 'arbitrarily takes or does not take precautions', and Panel C: 'never takes precautions'. The two valleys represent stable (as defined by the local curvature below the ball) attractor states with different depths. Hence, the system is more prone to perturbations when in the rightmost attractor (Panel A) and more stable when in the leftmost attractor (Panel C). The transition from one attractor to the other happens when the system crosses the unstable 'tipping point' in the middle (Panel B). Arrows in Panels A and C represent the amount of variability we are likely to observe due to random perturbations on the system, a proxy for its stability. Lower stability translates into likely higher variability in the system's state. Panel B also demonstrates that the landscape itself is not static but can change in the course of time (dashed line indicates the preceding landscape of panel A).

4. Change can happen in meaningfully different ways: gradually or abruptly. Continuous (gradual, smooth) transitions, and critical (abrupt) transitions roughly correspond to how change takes place in continuum and stage models in behaviour change, respectively. Emerging work in clinical psychology attempting to quantitatively distinguish between these categories (Helmich et al., 2020) shows that improvements often rather happen by jumps, than by a slow but steady crawl (as the linear approach would implicitly assume). Such work to rigorously evaluate types of change with intensive longitudinal assessments has not been widely done in behaviour change science, although it has been indicated that e.g., quitting smoking often takes place abruptly, and when it does so, it seems more persistent than when it happens gradually (Tan et al., 2019; West & Sohal, 2006).

Let us focus on critical transitions. Critical transitions can be further divided into two main types of tipping phenomena (Ashwin et al., 2012), which are of interest in the realm of behaviour change research. The first of these is *bifurcation-induced tipping ('B-tipping')*, where the attractor landscape changes over time, causing the system to eventually lose stability and move to a new attractor (see the left route of Figure 4). Metaphorically, it corresponds to the 'straw that breaks the camel's back', i.e., the fundamental disposition of the system changes until a critical 'mass' is reached and the system changes its state. For a person who has long considered stopping smoking, the news of an increased risk of death due to a new epidemic, could represent such a last straw, but the 'last straw' could equally well be a minor incidence. Or, during a smoking cessation counselling intervention over the course of several sessions, the client's self-concept changes from 'a person trying to quit' into 'an ex-smoker' – a previously identified powerful influence on behaviour (Meijer et al., 2020) – constituting a major shift in their smoking behaviour. As yet another example, the attractor landscape could shift radically due to a change in a person's environment, e.g., after moving to a new area and having to replace old social ties with new ones. The second class is *noise-induced tipping* (*'N-tipping'*), where random perturbative events cause the system to jolt to a new attractor (Ashwin et al., 2012; see also Proverbio, 2020). For example, a smoker may be 'forced' to not smoke in an airplane or a bar/restaurant, and the person has no choice – but the person may shift back to smoker state after this 'forced intervention'. It could be hypothesised that, if an intervention changes the 'inner core' of a person, i.e., changing the mental landscape altogether in a more permanent fashion, this could more likely be connected to B-tipping, whereas N-tipping is rather a result of external pressures imposed on the person or of temporary quirks.

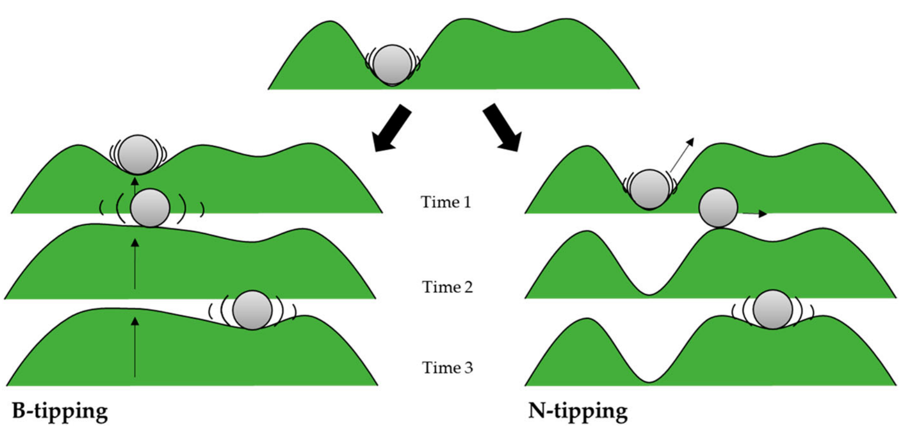

Figure 4. Two ways a system suddenly changes its state (i.e., two main types of critical transitions). B-tipping route (left): Due to an intervention or another learning or development process, the landscape itself changes, and when the state becomes unstable, the system 'tips' to the other attractor. N-tipping route (right): some exogenous perturbation, be it an intervention or a random event, jolts the ball over the threshold 'hill', where it stabilises in the new attractor.

Notably, Figure 4 makes it clear that the force required to return to a previous attractor is by no means necessarily the same as the force required to make the initial shift: Of the two examples presented, in the B-tipping case, the attractor is not available any longer (i.e., it is difficult for the person to return to the previous state and the newly adopted identity precludes any such behaviour, or there are practically no environmental opportunities left) – the transformation has occurred and cannot be reversed before the landscape changes again. In the N-tipping case, a minor perturbation might cause the system to revert to its previous state. When the shift from A to B, compared to that from B to A, is asymmetric, we speak of *hysteresis*, which is self-explanatorily exemplified by considering how much harder it is often to lose weight than it is to gain it back afterwards. In the same vein, if an individual enters the state depicted in Figure 3's Panel C ('never takes precautions to mitigate contagion'), much more needs to happen in order for them to change behaviour than if they reside in state depicted in panel A ('always takes precautions').

To give an example of the behaviour change process, familiar to health psychologists: The combination of influences on behaviour develops a landscape in which one attractor is 'smoking', the other one 'non-smoking'. Combinations of counselling interventions, environmental factors, access to tobacco products etc. could make the 'smoking' attractor more fragile (i.e., shallower). Hence, a small additional 'push' could make the system tip to the other attractor (non-smoking) – for example, pharmacological interventions stopping cravings (improving physical capability to resist temptations). However, if that new state is also rather shallow, another 'push' – even from random events such as facing some adversity or disappointment, or being offered a smoke by a colleague – could make the system tip back to the previous attractor (smoking). In such a way, the process of stopping smoking and relapsing can be explained as a combination of B and N-tipping. This way of conceptualising behaviour change connects it to what is known about change across living systems in other, more quantitative disciplines.

5. Resilience or stability of the system – and maintenance of behaviour change – depends on the depth of the valley (attractor). The ease with which a system switches from one attractor to the next, is defined by the local curvature under the ball in Figures 3 and 4. This stability among multiple attractors is dual to the concept of resilience, i.e., the ability to withstand adversities and return to original position after difficult events (also known as 'engineering resilience'), or not tip to a new regime (also known as 'ecological resilience') (Gunderson & Pritchard, 2012). In fact, a 'deeper' and 'steeper' valley makes it easier for a system to cope with perturbations (the ball has a harder time leaving its attraction basin and 'rolls back' faster); likewise, 'shallower' valleys reflect augmented fragility of the system state, which is more prone to jump onto a different state if perturbed. Note that, in many disciplines, resilience is not bound to a valence of the state the system resides in while, in psychology, resilience is generally understood to mean stability of a positive state. In behaviour change science, existing theories have focused on five influences as key explanations for behaviour change maintenance: 'the differential nature and role of motives, self-regulation, resources (psychological and physical), habits, and environmental and social influences from initiation to maintenance' (Kwasnicka et al., 2016). In the attractor landscape analogy, we would consider these five broad influences as shaping the new attractor to be deeper, and in that way facilitating maintenance of behaviour states.

A decrease in stability of the system – i.e., the attractor becoming shallower – can be hypothesised to result in increasing fluctuations in the values of a variable of interest. In the landscape analogy, when the ball is not confined by tight edges of a valley pressing against its sides, arbitrary forces can more easily move it around. Hence, flickering between states can indicate the shallowness of an attractor: When e.g., an individual is approaching a tipping point, or lies in a shallow attractor, this would be an optimal time for an intervention to take place, to either drive them to the tipping point or away from it, depending on which side the desirable state lies. Some readers may notice parallels to the unfreeze-freeze metaphor attributed to Kurt Lewin (Cummings et al., 2016); once such a critical 'unfrozen' regime is identified, concrete interventions to (de)stabilise a system's state could likely be derived from more conventional intervention development frameworks. 'Just in time adaptive interventions' are potentially very well suited to deliver such interventions, but continuous (e.g., daily) monitoring of the system in question is necessary. There is already applied work using this basic idea; for example, Olthof et al. (2019) discovered that increases in erratic fluctuation of psychopathological symptomology values in time series data predicted sudden shifts from one attractor to the next, and the same was observed in time series of step counts of people undergoing a weight loss intervention (Chevance et al., 2021).

In general, attractor landscapes provide a conceptual model which can be used for behaviour change problems regardless of what is the unit of analysis, how many attractors exist, and in how much detail they are described in. Although our examples above pertained to individual behaviour, it is important to realise that the same conceptualisation can be used to understand different scales of observation (dyads, small groups, organisations, societies). For example, a family can shift from a state of 'not recycling' to 'recycling', or a community from 'not condoning marital violence' to 'explicitly condoning marital violence'. On the level of a society, one of the attractors could represent a situation where most people are taking up pandemic precautions, and the other could be one where few are doing so. In this sense, the model bridges scales of interest to behaviour change researchers: The same idea can be used to describe any (psycho)social system. There is also nothing to limit the attractors to just two. To exemplify, Figure 5 below depicts several empirically derived phases – which can be considered as attractors – of pandemic precautions in a society.

Figure 5 illustrates two additional points about attractor landscapes: (1) That the number of attractors in a landscape is by no means limited to two, and (2) the concept can be used to infer dynamic patterns of societies as well as those of individuals. The data analysed in Figure 5 consist of eight variables describing COVID-19 protective behaviours in Finland, collected daily from a population of Facebook users (Astley et al., 2021; Barkay et al., 2020; Fan et al., 2020; Kreuter et al., 2020). Each variable indicates the percentage of respondents reporting the behaviour. In panel A, colours shown in the vertical slices are empirically derived phases of the population's behaviours during the COVID-19 pandemic, as defined by the configuration of behavioural variables in panel B, at different radius parameter values of Cumulative Recurrence Network Analysis (Hasselman & Hasselman, 2022) – also termed Multidimensional Recurrence Quantification Analysis in an earlier individual-level application (Heino et al., 2021). The analysis was carried out with the R package casnet (version 0.2.6; Hasselman, 2020). The horizontal axis values in Panel B indicate the percentage estimates of the country's population reporting high levels of the variables shown; each dot under the density plot represents a day, while the density plots indicate where the largest 'mass' of dots is located. Two attractors can be observed even with very strict standards over the radius values used to define vicinity within a recurrent network. The first is an attractor with few precautions, stemming from September 2021, when most restrictions were lifted despite community transmission of the Delta variant, to December 2021. The second is one with large-scale precautions, starting from Christmas Eve 2021 when large-scale gathering restrictions were put in place, to February 2022. Lower detection thresholds detect more nuance, e.g., a period of heightened precautions in the end of June 2021, when the Delta variant was initially and saliently imported by football fans returning to the country without quarantine or testing. The most obvious phases are also observed by Principal Component Analysis (PCA) in Panel C of Figure 5. PCA has the benefit of being widely known and potentially very useful in detecting movement between attractors, although it may be lacking in detecting movements and nuances farther from tipping points (Chen et al., 2019; Lever et al., 2020; Weinans et al., 2019). For details, we refer the reader to the technical appendix (https://heinonmatti.github.io/attractor-manuscript/).

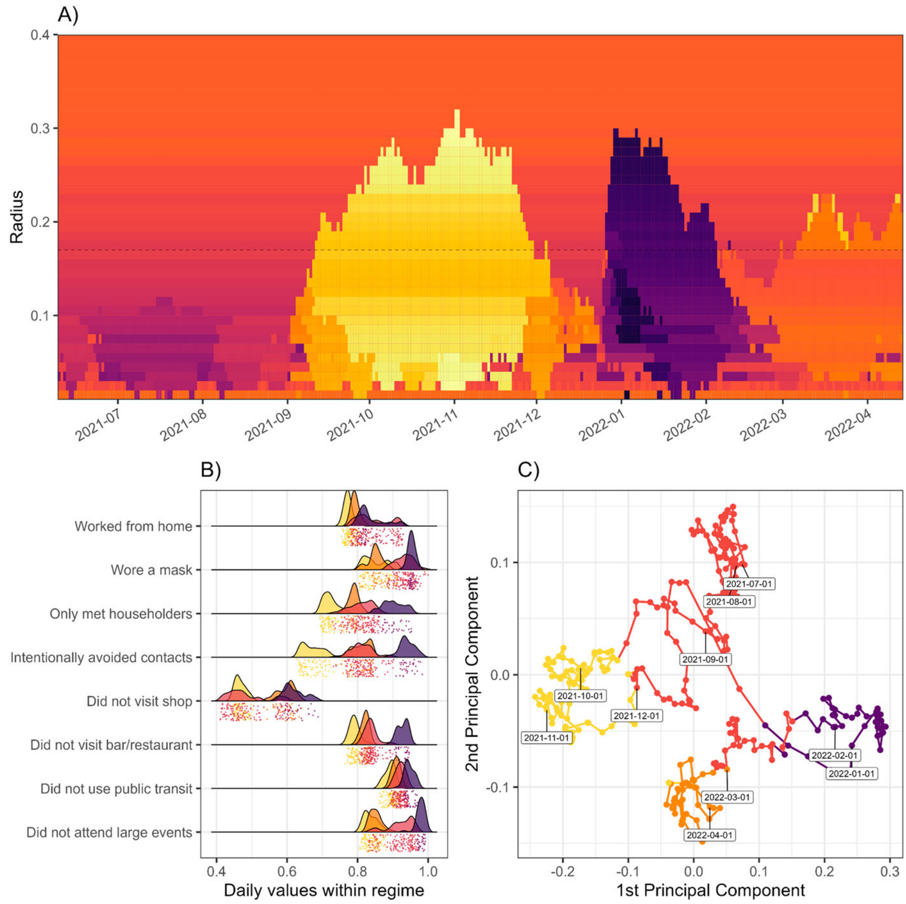

Figure 5. Demonstration of a society passing through several behavioural attractors during the COVID-19 pandemic. The underlying data are eight behavioural indicators collected daily in Finland (See text and supplementary website at https://heinonmatti.github.io/attractor-manuscript/ for details). Panel A: Reconstructing behavioural phases according to complex network approaches. Colours represent attractors for each day in the horizontal axis, with lighter colours indicating less precautions on average, and vice versa. The radius parameter defines a 'detection threshold' for the reconstruction of networks among the eight indicators; e.g., only the two most obvious attractors are observable on high radius values such as 0.25 (yellow area for lifting of restrictions despite community transmission of the Delta variant, and purple area for large-scale restrictions due to hospitalisations and deaths from both Delta and Omicron BA.1). Panel B: Raincloud plot of variables in the attractors, showing which values make up each regime at a representative radius (0.17), marked with a dashed line in Panel A. We can observe e.g., that each precaution is generally at its lowest during the yellow period, and highest in the purple period. As another example, we can also observe that people changed their shopping behaviour around the end of November, when the yellow regime ended. Panel C: Attractors reconstructed by Principal Component Analysis, as movement in the space of two main principal components (linear combinations of variables). The underlying conceptual model would correspond to Figure 2, but with four valleys instead of two. Colours to signify attractor types are imported from Panel B, at their corresponding temporal positions in Panel A, to illustrate convergence of the methods. The first principal component captures 68.4% of variance, and the second 20.3%.

Using attractor landscapes to understand complexity in behaviour change

Having now familiarised ourselves with the conceptual model of attractor landscapes, we can use it to connect behaviour change science to some fundamental features of complex systems, which have been discovered and characterised in other scientific disciplines. These principles originated in seemingly detached fields, but ones that, like behaviour change science, address systems with many self-organising interconnected parts and local interactions yielding surprising macro-scale phenomena (Mitchell, 2009; Siegenfeld & Bar-Yam, 2020). To make explicit the generality of these ideas across

Table 1. A selection of features of complex systems, with examples to highlight relevance to behaviour change science. See also 'The Visual Representation of Complexity' (2018) and Table 1 in Heino et al. (2021).

Complexity concept, and how it occurs in attractor landscapes	Examples over two levels (individual behaviour change and group-level behaviour change)
Emergence: The interplay of micro-scale components gives rise to macro-scale patterns, which are not observable from a more limited scope or by a reductionist approach. In an attractor landscape, when you observe a system for a long time, you can also observe new 'valleys' emerging. Similar processes happen when the boundaries of the system under study are drawn differently (e.g., including not just adolescents in an intervention, but also their families, introduces social dynamics which did not exist in the smaller scope).	Individual level: Instances of an individual's mask wearing behaviour gives rise to behavioural patterns (including automatic habits), which are not reducible to any particular instance of the behaviour, nor to a simple sum of all past behaviours. Group level: Individuals' mask wearing behaviours contribute to the emergence of (patterns of) social norms, which are not reducible to any particular individual.
Feedback loops: The outcome of a process acts to further accelerate or dampen a change process, creating 'vicious' or 'virtuous' cycles. In an attractor landscape, feedbacks which act to oppose a change (such as ingrained habits) yield steeper 'valleys', that make the ball roll back to the bottom. Instead, accelerative feedbacks (such as intrinsic motivation propelled by success in changing a behaviour) can be thought of as pushing over the barriers, onto new attractors.	Individual level: Success in changing a behaviour increases a person's intrinsic motivation to continue behaviour change efforts, further increasing the chances of success. Group level: In a public space where it is hard to keep a distance, people observe other people not keeping their distance, which leads to concluding that physical distancing is unimportant in the space, leading to fewer people physically distancing, and further reinforcing the crowdedness of the space.
Tipping points: A system can change little or not at all for a long time, until some threshold value is reached, and the system changes state radically in a relatively short period. In an attractor landscape, the system (i.e., the 'ball') reaches a 'hilltop' on the landscape and starts rolling to a new equilibrium.	Individual level: A person may hold persistent ambivalent attitudes and low intentions toward personal protective behaviours to mitigate contagion in the beginning of a pandemic. Stories of friends and family members getting seriously ill have seemingly little effect, until one day the person rapidly shifts their position. Group level: Support for an idea rapidly spreads beyond the initial vocal minority, after gaining sufficient salient acceptance in diverse social groups (e.g., 'complex contagion' processes in COVID-19 precautions; Centola, 2021).
Non-linearity: The outputs are not linearly proportional to the inputs, and large changes do not necessarily result from large events. In an attractor landscape, to leave a valley, a large change (jump) might result from large pushes from deep attractors, or from small pushes from de-stabilised states.	Individual level: Health promotion messages to change an attitude are unlikely to have the same impact on an individual when seen the first time, as compared to the 20th one, and changes in attitudes do not result in proportional changes in intention, yet alone behaviour. Group level: Consider a novel idea or a social representation. The speed of uptake increases or decreases depending on the current level of uptake, instead of remaining constant all the way through. See for example Figure 1; A single unit increase of time (x-axis), does not correspond to the same amount of increase in mask wearing (y-axis) throughout the period.
Sensitivity to initial conditions: Two systems which are almost identical, but differ in arbitrarily small quantities, can diverge wildly in their development as a response to an event (see Boeing, 2016 for an illustration). This implies fundamental problems to prediction, which additional data cannot solve in finite time. In an attractor landscape, a system close to b-tipping might jump or not, depending on whether it reaches its 'critical mass'. Any small value below it does not yield to tipping.	Individual level: Two persons, having filled in identical survey answers (by which an intervention is tailored to them), can still react to the intervention in different and unpredictable manners. Also due to this, the trajectory of an N-of-1 time series can be unpredictable beyond a very short time horizon (e.g., 3–5 time points in Olthof, Hasselman, & Lichtwarck-Aschoff, 2020). Group level: Two intervention sites can depict very different reactions to an intervention, based on the social dynamics embedded in their history – hence necessitating local community involvement in the design of complex interventions.
Hysteresis: The effort required to enter a particular state may be very different from the effort required to exit it. In an attractor landscape, the adjacent possible state may be vastly deeper than the current one, or vice versa.	Individual level: A habit of consistent physical activity can take months to build, but days to break (i.e., switch back to an inactive state). Group level: The simple act of reinstating a mask mandate after its initial removal, does not necessarily result in equivalent compliance, as observed during the initial mandate.

scales of observation (i.e., that the model applies to behaviour change problems regardless of the level under scrutiny), we provide examples on both the individual and the group level (see Table 1).

Studying complexity does not mean that we need to create spectacularly complex models accounting for all possible events and determinants, as well as their permutations and interconnections; that would be impossible in most if not all real-world applications (and would include massive sample sizes, as well as frequent and intensive per-person measurements). An alternative is to, rather, *complement* the research question of 'What is the causal chain from influences on behaviour to outcomes?', with questions such as:

– Is the system of interest residing in a shallow attractor, a deep one, or close to a tipping point? How close?
– Which matters more: What the intervention contains, how well it is planned, and how large is its dosage – or how close the system is to a tipping point?
– What are the sociopsychophysical phases this system (such as a person, community or society) wanders into? (For example, an individual can, in time, shift between 'balanced' and 'optimal' motivation profiles (Heino et al., 2021), and societies can shift between phases of uptake of protective behaviours, as indicated in Figure 5.)
– Which (behavioural) states are 'more attracting' than others? (For example, a control-oriented interaction style can, for some sports coaches, reside in a deeper attractor than an autonomy-supporting one.)
– If the person is in state x, how likely is it that they will transit to state y instead of state z? Will they move to a nearby state or one that's far away? (For example: will an 'ex-smoker' relapse into 'occasional smoker' or 'heavy smoker' status?)
– If persons are exposed to random unexpected events, will they likely shift to a better state or a worse one?

While the results may at first seem less satisfactory than understanding full causal mechanics of a health behaviour process, it is an attractive way of doing practical, empirical behaviour change science, as the pursuit of causality is almost certainly not as simple as conventionally understood (Heino et al., 2021; Sugihara et al., 2012). The promise is that, even when intervention developers have little information about the components (e.g., influences on behaviour, or determinants, if we are looking at the behaviour of a single individual, or singular individuals if we are looking at the behaviour of a community), they can still infer important, holistic propensities of the system. Such propensities include the system's overall stability, indicating amenability to change efforts, as well as risk of adverse outcomes: If a beneficial state becomes unstable, or 'unfreezes' in Lewin's classical terms (Cummings et al., 2016), this indicates that steps ought to be taken to prevent the system from sliding to an undesirable state. Likewise, if an undesirable state de-stabilises, this critical period can be used to e.g., time an intervention or choose its participants.

Using the conceptual framework of attractor landscapes as an entry point to complexity thinking, novel facets affecting design of interventions arise. The close connection with mathematical theories can unravel a set of quantitative tools that could concur in validating the suggested behavioural models by making quantitatively testable predictions.

Given what has been learned in natural sciences, and how these features have been repeatedly observed in human physiology and cognition (Wijnants, 2014), as well as in series of psychological self-reports (Heino et al., 2021; Olthof, Hasselman, & Lichtwarck-Aschoff, 2020), it is reasonable to ask, upon whom lies the burden of proof for the applicability of analytical tools used – the user of conventional methods of analysis, or the one who calls for a change in perspective? There is a plethora of empirical tools to study falsifiable hypotheses about whether a time series is generated by a complex system – for example, linear systems do not exhibit hysteresis; hence if hysteresis is observed, the use of linear models should be seriously discussed. As a concrete example, most behavioural scientists would agree that adopting a healthy behaviour is often more difficult than stopping it, and that maintenance of health behaviour change over the long term is more difficult than initiation. Therefore, such phenomena of behaviour change seem to be characterised by hysteresis – thus implicating a non-linear system. Or, if rapid regime shifts are present, conventional autoregressive models are not suitable to describe nor to predict systems' states. In other words, where the system's behaviour is characterised by fluctuations between multiple stable regimes, statements such as 'intentions at previous time point are correlated with behaviour at the next time point, $r = 0.3$' contain little meaning. Moreover, in determining the evolution of certain systems, not only the position in the state space might be important, but also the system's rate of change and its historicity ('the importance of how you got there'; Ashwin et al., 2015); they both can determine responses, stability and critical transitions. Consider, for example, if at baseline, two people weigh 70 kilograms, but a year ago one of them was 170 kilograms and the other 50 kilograms: we can expect quite different reactions to an intervention, although they are, nominally, at the same starting point. While some designs such as N-of-1 trials have been documented at length (see e.g., Kwasnicka et al., 2019), others are perhaps less known. Hence, we include a brief description of the Multiphase Optimisation Strategy (MOST), Sequential Multiple Assignment Randomised Trials (SMART), Micro-Randomised Trials (MRT), and Reinforcement Learning (RL) in the supplementary website (https://heinonmatti.github.io/attractor-manuscript/). In a way, adaptive interventions learn like evolution does: through fast cycles of iterative development, and in essence, feedback loops.

Future avenues for behaviour change research

Bridging current behaviour change theory with that of attractors in dynamical systems presents exciting future avenues for multidisciplinary research. The literature has identified several relevant factors related to changes in systems' robustness, which will aid research collaboration between behaviour change science and complex systems science. These include changes in skewness, added response-lag or resistance to change, flickering (quickly moving from one state to another), as well as increased variance and autocorrelation (i.e., how much does a subsequent time point depend on the value of the preceding one) (Dablander et al., 2022; Olde Rikkert et al., 2016; Stapelberg et al., 2018). As the mathematical underpinnings are a common denominator with other natural systems, results from other fields (Allen, 2011; Gardiner, 2002; Goldenfeld & Goldenfeld, 2019; Kuznetsov, 1998) could also be transferred and applied relatively easily and effectively, to generate novel hypotheses and to guide the development of more refined analysis methods. Moreover, it is the focus of current multidisciplinary research programmes and of future studies to derive better proxies of system robustness from theoretical models, to justify and interpret them appropriately, and to assess how reliable they are as indicators to be used in real-world risk assessment routines – and in which situations (Proverbio et al., 2022; Zhang et al., 2015).

Researchers looking for practical applications may be interested to e.g., find out why even when behaviour change interventions work in making people change their behaviour initially, they often lack long-term effects. Is this a signal that an N-tipping process has taken place? Or that the 'arrival' attractor was not deep enough for most participants? Eventually, it might be possible to infer from data, which type of tipping has taken place, so that persons who have reached a stable attractor are deemed to have received a satisfactory intervention dosage – one's 'inner core' has changed, or one's environment has drastically changed (by removing behavioural options). Hence no further intervention may not be needed. Conversely it could be hypothesised that, if the attractor is shallow and/or an N-tipping process has taken place, it might be worthwhile to continue the intervention. As another possible future avenue, work would be needed to understand how to best destabilise an individual's social psychological system for positive change to occur, and how to re-stabilise the newly arrived-at desirable attractor states – commonly known as 'behavioural maintenance'. The results can be informative about e.g., which individuals are more likely to be sensitive to an intervention targeting a specific behaviour, and when is the time conducive to such change attempts. This also provides the theoretical underpinning for the movement towards precision health (Hekler et al., 2020).

Discussion

In this paper, we have argued that behaviour change science ought to begin a discussion with fields of science, which have been studying the intriguing commonalities between different systems undergoing complex changes. The initial step we propose in doing this, is understanding behaviour change through the lens of attractor landscapes, which can depict behavioural states, phases, or even 'stages' (as understood in stage theories of behaviour change). We hope to have bridged the conceptual model of landscapes, which hails from mathematical underpinnings, with intuitions of behaviour change researchers, by pointing out how factors such as motivation, drive, pleasure, addiction, social norms, and inertia (or lack thereof) can mould the valleys of the landscape – also called attractors – while salient events or critical incidents can push the system to another valley.

Some further points deserve highlighting. First of all, the shape of the landscape informs us of certain assumptions: Without a rugged landscape, there's no possibility to have tipping (abrupt change), but only continuous, gradual transitions are allowed. A flat state space can be fully explored by the system with equal probability (by definition), with change exhibiting as continuous transitions, and represents the ideal case for linear methods of analysis. Secondly, the landscape informs that the action of interventions, although maybe not showing immediate and proportional results, is in de-stabilising an unwanted behaviour and/or in 'deepening' a wanted one – that is, facilitating or hindering *b-tipping*. Interventions with short-term effects, including nudges and those relying on controlled forms of motivation (Hagger, Hankonen et al., 2020) could be hypothesised to work through the process of *n-tipping*.

Third, the landscape metaphor makes sense of the asymmetry regarding the ease of relapse compared to behavioural initiation, and ease of behavioural initiation compared to behavioural maintenance. That is, it takes more time to convince persons to quit smoking for the first time, than for them to relapse: this can be interpreted as asymmetry in attractors (one being deeper than another).

Fourth, the landscape lends credence to the widely held observation, that initiating the behaviour is not sufficient for sustained behaviour change: as the attractor can still be quite shallow, stabilisation (i.e., maintenance) may need as much effort as initiation. This explains why maintenance of behaviour change is so difficult; the newly acquired state may be so shallow that bouncing back is very easy. The attractor landscape metaphor may thus be helpful in assisting intervention participants identify key factors or processes that help 'deepen' the desired valley (the target behaviour state) and block 're-entry' to the undesired state.

Fifth, when the attractor in question is a desirable one, its stability is a direct analogy to the concept of resilience: Resilient people or other systems bounce back to their initial desirable (or an improved) state, instead of rolling over the 'hill' to an undesirable attractor.

Sixth, having mathematical underpinnings from other fields studying physical and living systems, the landscape constitutes a quantitatively testable framework (e.g., the frequency of relapsing, its timing, or other measurable facets), as well as providing a shared conceptualisation for interdisciplinary work.

Lastly, the landscape model is an epistemologically humbling idea: In the linear case of a flat terrain of points visited with equal probability (continuous transitions), the past is a good indication of the future. But in the non-linear case, even though a new valley has hitherto not been observed, it does not mean that one does not exist, and apparent stability can be followed by a large sudden shift.

Conclusion

Throughout the history of science, it has been learned that 'methodological reductionism, the analytical decomposition of structures to parts, should be completed by searching for organisational principles, too.' (Erdi, 2008). Hence, behaviour change researchers will miss part of reality, unless they start paying attention to how things unfold (dynamics), in addition to looking for forces which make them unfold. In the context of behaviour change science, these forces are the determinants. They have been studied intensively but, to our knowledge, few scholars have yet questioned how they relate to state *stability* (i.e., depth of the valley) of a person (or other systems) and whether the latter could be a highly relevant feature to understand and guide change, along with – or even beyond – interventions that are matched to the determinants alone. Rather than suggesting to revert the focus from determinants (or 'influences on behaviour') to dynamical properties only, we call for complementing studies that may connect the two aspects, reductionist and holistic, to unravel the dynamics of behaviours. This approach would complement current studies by learning 'how things evolve', in addition to '*what* makes things evolve'. For example, this could be done by harnessing the understanding of how stable or unstable the potential states are over time, and how to strategically create instability – shape the landscape – to enable better readiness for change (tipping).

There is already a fertile ground for new developments in behaviour change science, with a recently increased use of existing N-of-1 methods and intervention tuning approaches therein. However, the focus on the scale of an individual hinders immediate usefulness when fast, large-scale behaviour change among entire populations is warranted (e.g., during a pandemic). Hence, models of how to understand behaviours at both small and large scales can aid in guiding our thought towards more generalisable knowledge, with the additional benefit of being compatible with other scientific disciplines. Humans are, after all, complex systems whose behaviours are meaningfully affected by a vast range of factors, many of which unknowable in practice. Such systems have been studied in other fields of science, where the system under study can be learned from via dynamical signals and their useful features. The conceptual metaphor of psycho-socio-behavioural attractor landscapes, which are shaped by multiple personal, social, and environmental factors, provides one such interdisciplinary bridge. We hope to have shown that there exist as-to-yet uncharted possibilities in applying this approach to behaviour change science. Its increased uptake will fruitfully complement our current approaches and may help us fare at charting uncertainties, better prediction, more accurate explanations and eventually, more successful behaviour change interventions.

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Data availability statement

Data is available on the GitHub repository online: https://github.com/heinonmatti/attractor-manuscript.

Supplementary materials

The supplementary website describing the methodology to reproduce Figure 5, as well as introducing adaptive trial designs, is at: https://heinonmatti.github.io/attractor-manuscript/

Reporting

All analyses and code are available on the GitHub repository online: https://github.com/heinonmatti/attractor-manuscript.

Author contributions following CRediT

Conceptualization: MTJH & DP & NH & GM & KR, Methodology: MTJH & DP, Software: MTJH, Validation: MTJH, Formal analysis: MTJH, Investigation: MTJH & DP, Resources: MTJH, Data Curation: MTJH, Writing – Original Draft: MTJH & NH, Writing – Review & Editing: MTJH & DP & NH & GM & KR, Visualization: MTJH & DP, Supervision: NH, Project administration: MTJH & NH, Funding acquisition: NH & MTJH.

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