The Nonmechanistic Option: Defending Dynamical Explanations

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Abstract

This paper demonstrates that nonmechanistic, dynamical explanations are a viable approach to explanation in the special sciences. The claim that dynamical models can be explanatory without reference to mechanisms has previously been met with three lines of criticism from mechanists: the causal relevance concern, the genuine laws concern, and the charge of predictivism. I argue, however, that these mechanist criticisms fail to defeat nonmechanistic, dynamical explanation. Using the examples of Haken *et al.*’s ([1985]) HKB model of bimanual coordination, and Thelen *et al.*’s ([2001]) dynamical field model of infant perseverative reaching, I show how each mechanist criticism fails once the standards of Woodward’s ([2003]) interventionist framework are applied to dynamical models. An even-handed application of Woodwardian interventionism reveals that dynamical models are capable of producing genuine explanations without appealing to underlying mechanistic details.

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8. Introduction

This article demonstrates that mechanist objections to nonmechanistic, dynamical explanations are unsuccessful, as they do not hinder dynamical models from being genuinely explanatory. The justification for this defence comes from the even-handed application of interventionism (Woodward [2003]) which will be shown to be a viable framework for both mechanistic and nonmechanistic accounts of explanation.[[1]](#footnote-1) By applying the interventionist framework (specifically the notions of ideal interventions, invariance, and counterfactual explanation) in an even-handed way to dynamical models, it is shown that nonmechanistic, dynamical explanations are not deflated by these critiques. Moreover, Woodwardian interventionism provides the foundations for a fully-fledged account of nonmechanistic, dynamical explanation.

Some critics, mechanist or otherwise, may argue that there is something wrong with the interventionist account offered by Woodward (or simply take a neutral stance towards it) and may be unswayed by my arguments since the whole enterprise of interventionism seems suspect or unconvincing. My goal here is however not to offer a broad defence of Woodward. Interventionism is not necessarily the hill I intend for nonmechanistic explanation to die on. The aim of this paper is rather to make the case that for mechanists who do agree with interventionism (and there are many), and who ­rely heavily on it for their own accounts (and many do), they must accept that nonmechanistic models like dynamical models can also explain.

The scope and application of mechanistic explanation is a major contemporary topic of discussion in philosophy of science (Boone & Piccinini [2016]; Bechtel [2017]; Chirimuuta [2017]; Mathiesson [2017]; Craver [2017]). Since the earlier and more restrictive iteration of mechanism laid out by Machamer, Darden & Craver ([2000]) mechanism has been increasingly extended in scope. Its proponents claim that mechanistic explanation­­­s are applicable across a broad range of domains, including systems and cognitive neuroscience (Zednik [2014], Boone & Piccinini [2016]), systems biology (Mathiesson [2017]), cognitive science (Bechtel & Abrahamsen [2010], [2013]) and psychology (Piccinini & Craver [2011]). This encroachment on new domains has in turn resulted in disagreements over how appropriate mechanism is to these ‘special sciences’, with some critics preferring to advance varieties of nonmechanistic explanation (Weiskopf [2011]; Dupré [2013]; Brigandt *et al.* [2018]).

While critics differ in their rationale for preferring a nonmechanistic approach to explanation[[2]](#footnote-2), there is a common feeling among these dissenters that mechanistic explanations are not suited to the kinds of nondecomposable, nonlinear or otherwise complex phenomena that are frequently investigated by biologists, cognitive scientists and psychological scientists.

One particularly vocal source of nonmechanistic criticism of mechanism comes from proponents of dynamical modelling, some of whom claim that dynamical models are better suited to some phenomena in cognitive science, psychology and related domains than mechanisms (Chemero & Silberstein [2008]; Stepp Chemero & Turvey [2011]; Silberstein & Chemero [2013]; Lamb & Chemero [2014]). It is this dynamicist tendency that I will focus on in this article.

Contra the dominant mechanist trend, these dynamicists argue that dynamical models can explain by abstracting away from the mechanistic details of a system and describing highly predictive mathematical models of a systems’ behavi­our. One influential branch of dynamicism advocates for a revival of covering-law explanation (Walmsley [2008]; Gervais & Weber [2011]; Stepp et al. [2011]). This attempt at building a dynamical, covering-law mode of explanation has become widespread enough to be deemed the ‘received view’ (Zednik [2011], pp. 239) amongst dynamicists about how dynamical models could explain. The attempted revival of covering-law explanation has subsequently been criticized heavily by mechanists (Bechtel [2011]; Craver & Kaplan [2011]; Kaplan & Bechtel [2011]; Kaplan & Craver [2011]) who consider it to be a flawed approach to explanation, and one that retains the existing flaws in law-based explanation.

This paper is structured as follows: Section 2 outlines mechanistic explanation and Woodwardian explanation, and Section 3 will similarly outline dynamical modelling and the covering-law mode of explanation using the example of the HKB model of bimanual coordination. Sections 4, 5 and 6 then identify and respond to the criticisms made by mechanist, interventionist philosophers and directed towards proponents of dynamical covering-law explanation. Three lines of criticism will be investigated – the genuine laws concern, the causal relevance concern, and the error of predictivism on the part of dynamicists. In Section 7 I address Woodward’s criticisms of the HKB model in particular as explanatory within an interventionist framework. Section 8 puts these solutions together into a coherent whole, showing how an account of dynamical explanation would work.[[3]](#footnote-3)

1. Interventionism and Mechanistic Explanation

I will outline a few key aspects of Woodward’s account of explanation ([1997], [2003], [2002], [2008], [2013a]) namely ideal interventions, the notion of invariance, and counterfactual explanation. In addition, I will show how mechanists appeal to Woodwardian interventionism, and incorporate it into mechanistic explanation. The foundation of much mechanist thought is Craver’s ([2007]) influential account of mechanistic explanation, which in turn heavily integrates Woodward’s notions of ideal interventions, invariance and counterfactual explanation. Craver’s account has in turn been integrated by a wide range of mechanist philosophers (Bechtel [2008]; Darden [2008]; Piccinini & Craver [2011]; Zednik [2011], [2014]; Bechtel & Abrahamsen [2010], [2013]; Bechtel & Richardson [2010]; Kaplan [2015]). When speaking about mechanists or mechanistic explanation in this section, I am referring to this contingent of mechanist thinkers and their approach to explanation.

* 1. Causal relevance & ideal interventions

The issue of causal relevance has caused difficulties for several accounts of explanation.[[4]](#footnote-4) If an explanation is unable to distinguish which facts are causally relevant (and should be included in the explanation) and which are causally irrelevant (and should be excluded) then it will fail to properly explain. Explanation requires a description of the causal structure (Salmon [1984]) that resulted in the explanandum phenomenon – and describing the causal structure requires a clear picture of what features of the world are causally relevant.

Woodward differentiates causally relevant features of an explanation from causally irrelevant ones by employing an interventionist framework. Woodward’s claim is that ‘causal (as opposed to merely correlational) relationships are relationships that are potentially exploitable for purposes of manipulation and control.’ (Woodward [2008], pp. 219). Those relationships that can be possibly intervened on are causal relationships, and relevant from an explanatory standpoint.

This process is formalized by Woodward as:

(M) X causes Y if and only if there are background circumstances B such that if some (single) intervention that changes the value of X (and no other variable) were to occur in B, then Y would change. (Woodward [2008], pp. 222).

Establishing causation therefore requires finding relationships that can be manipulated. Here manipulation is cast as an ideal intervention. An ideal intervention is a manipulation made on the value of a variable, and it is idealbecause the intervention needs to be possible in principal, but not necessarily in practice. The target might be too big, too small, too far away, or in some other condition that makes an actual intervention impossible. Woodward makes this point to avoid an anthropocentric concept of causation and intervention – causation would still be a feature of nature without humans around, and interventions occur all the time without the involvement of humans. An intervention on X ought also to isolate its effect on Y and eliminate confounding variables.

Mechanistic explanations make heavy use of Woodward’s notion of an ideal intervention for establishing causal relevance:

To say that one item (activity, entity or property) is relevant to another, is to say, at least in part, that one has the ability to manipulate one item by intervening to change another. (Craver [2007], pp. 93-94)

The use of ideal interventions is a crucial aspect of mechanistic explanation: Craver claims that Woodward’s account of causal relevance provides “an essential normative component to previous counts of mechanistic explanation” (Craver [2007], pp. 105) marking it as an improvement over the previous mechanist accounts produced by Glennan ([1996]), Machamer *et al.* ([2000]) and Bechtel & Richardson ([2010]).

* 1. Invariance

The next component of Woodward’s account is invariance, a measure of both the stability and causal potency of a generalisation, and that bears some resemblance to the notion of a law of nature. While Woodward ([2003]) does not consider laws of nature to be crucial to explanation, he is however keen to distil out something useful from the notion of laws. What laws do for explanation, Woodward claims, is to provide stable generalisations that hold between a collection of variables. The problem of distinguishing a generalisation from a bona fide law of nature is a moot point, since Woodward argues that lawfulness is not really the useful or interesting property of a given generalisation. The truly important distinction is between generalisations that are accidental, and those that are invariant.

Accidental generalisations (everyone in this room is currently sitting down; every coin in my pocket is silver) are unstable, do not expose causal relationships and are hence not particularly explanatorily useful. Distinguishing merely accidental generalisations from more stable and explanatory useful generalisations is, for Woodward, conducted by establishing the invarianceof these generalisations:

Because invariance is the key to explanatoriness, we don’t need to decide whether a generalization counts as a law (and hence we don’t need to find a sharp dividing line between laws and nonlaws) to distinguish between the explanatory and the nonexplanatory. (Woodward [2003], pp. 183-4)

[[…]]it follows that whether or not a generalization can be used to explain has to do with whether it is invariantrather than with whether it is lawful. (Woodward [2000a], pp. 2)

How can invariance be established?

A generalization is invariant if (i) it is […] change-relating and (ii) it is stable or robust in the sense that it would continue to hold under a special sort of change called an intervention. (Woodward [2000a], pp. 198)

Establishing invariance necessarily requires the use of interventions. Both (i) and (ii) involve the application of interventions. In the case of (i) the goal is to establish that this set of relationships between variables depicted in the generalisation is ‘change-relating’ (also known as ‘difference-making’ – both are synonyms of causally relevant).

This criterion eliminates the kinds of accidental cases discussed earlier. For instance, the case where being present in this room (P) is related to sitting down (S), the truth of P relates to the value of S. However, this generalisation breaks down if we intervene on P and S and observe their effects on one another – someone could stand up while remaining in the room, or be outside the room but sitting. This relationship between P and S is merely accidental, and we cannot explain the value of P or S by citing this relationship.

For criterion (ii), Woodward also states that this relationship needs to demonstrate stability, and show that it holds under a ‘range of interventions’. The more stable the relationship, the more explanatory ‘depth’ is established, meaning a broader range of scenarios under which the generalisation continues to provide explanatory power. It is important to note that neither stability (and hence invariance) is a binary condition, but rather stability ‘admits of degrees’ (Woodward [1997], pp. 34). A generalisation that remains stable over a great range of interventions is explanatory over a greater range of scenarios, but this does not exclude less stable generalisations from explaining within a narrower range of conditions.

Invariance is a key part of mechanistic explanation, and there is a broad acceptance by mechanists that ‘interactions in a mechanism should be characterized in terms of invariant change relating generalizations’ (Kaiser & Craver [2013], pp. 25). Craver claims that mechanistic explanation ‘[relies] closely on James Woodward’s account of the role of invariance in explanation’ (pp. 94), and integrates the criteria of change-relating and stability as important for explanatory power:

[…] causal relations need not be universal to be explanatory, nor need they be unrestricted in scope, nor need they lack any reference to particulars. All that matters is that there is some stable set of circumstances under which the variables specified in the relation exhibit the kind of manipulable relationship sketched above. (Craver [2007], pp. 100).

* 1. Explanation

So far, we have seen how interventions establish the causal relationships between variables, and that these kinds of causal relations can be captured and described systematically in the form of invariant generalisations. In addition, mechanistic explanations make use of both ideal interventions and invariance in order to provide explanatory accounts.

Following from this, Woodward claims that “explanation is a matter of exhibiting systematic patterns of counterfactual dependence” (Woodward [2003], pp. 191). Once we know the “systematic patterns” (the invariant generalisations) at work in producing a phenomenon, we can also investigate counterfactual scenarios. Knowing what happened, and what would have happened if circumstances had been different (counterfactual dependence) is the key to explanatory power.[[5]](#footnote-5) A model that provides a combination of a description of the invariant generalisations at work, and predictions of what would happen in counterfactual scenarios based on the description of those generalisations, is explanatory. Explanations in the Woodwardian sense can tell us why things obtain, and what would have happened had circumstances been different.

Mechanistic explanations also utilize counterfactual notions of explanation. A mechanism shows the counterfactual dependencies operating between its components (a collection of invariant generalisations between components), and in this way, provides an explanation of why a certain phenomenon occurred, and how things would have occurred in different conditions.[[6]](#footnote-6)

1. Covering-Laws and Dynamical Explanation
   1. Dynamical models

Dynamical models are a kind of descriptive model used to investigate systems by way of the mathematical tools of dynamical systems theory (DST). The techniques of DST developed out of the field of synergetics (Haken [1983]; Kelso [1995]), and have come to be applied across a wide variety of domains including circadian rhythms (Bechtel & Abrahamsen [2009], [2010], [2013]); infant locomotion (Thelen & Smith [1994]) and reaching behaviour (Thelen *et al.* [2001]; Smith & Thelen [2003]); robotics and artificial intelligence (Beer [1995]); human coordination (Haken *et al.* [1985]; Mechsner *et al.* [2001]); and cellular genetics (Huang *et al.* [2005]). At the heart of these models are differential equations which model the often nonlinear and highly complex relationships between those variables.

The Haken-Kelso-Bunz (HKB) (Haken *et al.* [1985]) model of bimanual coordination is a frequently invoked example of a dynamical model (Kelso [1995]; Stepp *et al.* [2011]; Chemero [2011]; Lamb & Chemero [2014]; Kaplan [2015]). The HKB model is a dynamical model that attempts to describe the phenomenon of bimanual coordination. Bimanual oscillations (‘wagging’ the index fingers of both hands at the same time) can be conducted in either in-phase or anti-phase conditions.

The differential equation used in the HKB model:

Here 𝜙 is relative phase, having a value of either 0 degrees or 180 degrees (representing in- and anti-phase conditions respectively) and *b/a* is the coupling ratio inversely related to the frequency of oscillations.

The variables in the HKB equation track abstract mathematical features of a system, and show how the system would behave over time given certain input values. In practice, the HKB model and other dynamical models are often highly accurate descriptors and predictors of the modelled system’s behaviour (Chemero & Silberstein [2008]; Chemero [2011]; Silberstein & Chemero [2013]).

Using the HKB model as an exemplary case, this section will examine two properties ascribed to dynamical models: that they provide covering-law explanations, and that their predictive power is indicative of explanatory power.

* 1. Covering-law explanation

Many dynamicists have claimed that dynamical models like the HKB model can be more than merely descriptive, and can provide genuinely explanatory accounts of phenomena (Kelso [1995]; Van Gelder [1995], [1998]; Bressler & Kelso [2001]; Chemero & Silberstein [2008]; Walmsley [2008]; Stepp *et al.* [2011]; Silberstein & Chemero [2013]; Lamb & Chemero [2014]).[[7]](#footnote-7)

One common claim is that dynamical models produce something like lawful statements about systems:

[…] the brain is fundamentally a pattern forming self-organized system governed by potentially discoverable, nonlinear dynamical laws. (Kelso [1995], pp. 257)

The same sentiment is echoed in Bressler & Kelso ([2001]), who argue that the HKB model ‘exemplifies a law of coordination that has been found to be independent of the specifics of system structure’ (pp. 28).

These dynamicists are invoking a long-standing conception of explanation as being based on laws of nature. An influential account of how laws explain comes in the form of the covering-law model of explanation (Hempel & Oppenheim [1948]; Hempel [1962a]; [1965]). The covering-law model suggests that:

## [An] explanatory account may be regarded as an argument to the effect that the event to be explained […] was to be expected by reason of certain explanatory facts. These may be divided into two groups: (i) particular facts and (ii) uniformities expressed by general laws. (Hempel [1962a], pp. 10; quoted in Salmon [1984], pp. 19).

Hence a covering-law explanation ought to provide a set of facts governed by a law, and show how a logical necessity holds between these facts and the governing law. For instance, the orbit of a planet is governed by Kepler’s first law:

L1. The orbit of a planet is an ellipse with the Sun at one of the two foci.

We can combine the antecedent facts (the location, velocity and acceleration of the planet as well as the location of the Sun) with Kepler’s first law and show that the planet’s orbit was to be expected based on these facts. This set of facts combined with this law would qualify as an explanation of the planet’s orbit under the D-N model.

Walmsley ([2008]) attempts to fit dynamical accounts into this covering-law mode of explanation:

[…] the explanatory goal of dynamical cognitive scientists is to provide covering-law explanations whereby a cognitive phenomenon is explained by way of citing the laws (qua differential equations) that govern the system that produces it. (pp. 344).

The central claim from Walmsley is that the equations used in dynamical modelling can become explanatory within the context of a covering-law explanation. Dynamical equations such as those used above can act as governing laws for the system they represent, and they describe a logical necessity operating between the antecedent conditions and the equation much as laws of nature do in Hempel’s account.

Depending on our interests, then, we can insert the values we know into the equation, and solve the equation in order to find the values we do not know. Finding the values for *a*, *b*, and 𝜙 when *d*/*dt* is 0 would constitute to an explanation of why *d*/*dt* takes the value it does […] (Walmsley [2008] pp. 341).

An explanation produced using this method would have explanatory power because it can tell us how, based on the logical necessity operating between the values of the variables *b*/*a* and𝜙 that the result was to be expected.

* 1. Prediction

In addition to claims about covering-law explanation and dynamical models, some dynamicists have claimed a direct connection exists between the predictive powers of dynamical models like the HKB model and their capacity to explain phenomena. The HKB model accurately predicts several important outcomes of bimanual coordination, namely that there will exist two stable basins of attraction at low frequencies (in- and anti-phase), as well as phase switching at certain critical values of *k* (Kelso [1995]; Walmsley [2008]). Chemero & Silberstein ([2008]) argue that this predictive power is an indicator of a deeper explanatory power:

If models are accurate enough to describe observed phenomena and to predict what would have happened had circumstances been different, they are sufficient as explanations. (pp. 12).

This claim also appears in Walmsley’s account, where he attributes explanatory power to predictive models like the HKB model. This is justified by a quirk of the covering-law account:

[…] the only difference between a prediction and [a covering-law] explanation is whether or not the state of affairs described in the explanandum is known to have obtained. It is therefore solely a pragmatic difference—prediction and explanation have an identical logical structure, but differ in terms of what one knows and what one wants to know. (Walmsley [2008] pp. 340).

In the same vein, Stepp *et al.* ([2011]) also claim that ‘[…] dynamical explanations show that particular phenomena could have been predicted, given local conditions and some law-like general principles […]’ (pp. 432). They also note the significance of the counter-factual supporting nature of the model, since “we can use the mathematical model to make predictions of the activity of the slave system with so-far-unobserved activity in the master system.” (pp. 432). In their view, this combination of prediction and counterfactual support is explanatory within the context of a covering-law explanation.

What follows in Sections 4, 5 and 6 are three lines of criticism presented by mechanist philosophers who are critical of the possibility of dynamical explanations that appeal to the covering-law model.

1. Causal Relevance
   1. The causal relevance concern

The causal relevance concern regards the apparent inability for dynamical explanations to establish causal relevance, and is a development of long standing criticism of covering-law explanations. While an interventionist approach allows mechanistic explanations to determine causal relevance, covering-law explanations have no comparable technique. Covering-law explanations are therefore at risk of excluding causally relevant variables, and including causally irrelevant variables – there is effectively no way of knowing which variables are relevant to the explanation and which are not. They cannot tell us about the causal structure that produced a phenomenon (Salmon [1984]).

Without an account of causal relevance, we cannot give a causal account of why a phenomenon occurred, since “[…] the line that demarcates explanations from merely empirically adequate models seems to correspond to whether the model describes the relevant causal structures that produce, underlie, or maintain the explanandum phenomenon.” (Craver & Kaplan [2011], pp. 602). Dynamical models do not by themselves tell us anything about causal structure, and so according to this critique they remain in the category of descriptive models, without explanatory power.

Craver & Kaplan ([2011]) claim that this flaw in covering-law explanation is generally accepted and long standing, stemming from critics of the covering-law approach like Salmon ([1984], [1989]). Their rejoinder to dynamicists on causal relevance is a “reminder from the past 6 decades of philosophical work on scientific explanation” (pp. 602) that explanations need to provide an account of the causes of a phenomenon, not just describe it. Since causal relevance remains a problem for covering-law explanation:

[…] there is no currently available and philosophically tenable sense of ‘explanation’ according to which such models explain even when they fail to reveal the causal structures that produce, underlie, or maintain the explanandum phenomenon. (Craver & Kaplan [2011] pp. 602)

Hence dynamical explanations would be at best merely descriptive pseudo-explanations, which fail to identify the causal relationships among variables.

* 1. Intervening on dynamical models

I argue contrary to Craver & Kaplan ([2011]) that dynamical models can in fact provide facts about causal relationships, and ultimately explain. There are no grounds on which to assume that dynamical models cannot also utilize Woodwardian interventionism to establish causal relevance. While mechanist philosophers consider mechanisms to be the best subject for the interventionist framework, Woodward’s account is shown here to also be useful to a nonmechanistic and dynamical account of explanation.

For mechanists who are proponents of Woodwardian interventionism, causal relationships are those relationships that can be exposed via ideal interventions. Mechanisms are essentially bundles of causal relationships, and experimental interventions are necessary to show how a component is causally relevant to the mechanism, and thereby reveal those causal relationships. Describing these relationships is the basis of explanatory power.

By applying this same Woodwardian notion of ideal interventions to dynamical models, the causal relevance concern can be countered. If we can intervene on the values of variables in a dynamical model, and see changes in the value of another variable, then (on the interventionist account) we have exposed a causal relationship. I am not arguing for any modification to Woodwardian interventionism – rather, I am arguing for its application outside of just mechanistic models and explanations, something which Woodward’s account is perfectly capable of doing.[[8]](#footnote-8)

* 1. Test case I: The HKB model

In order to test out this argument, I will consider empirical studies of the HKB model and determine whether they represent successful interventions that exposed causal relationships within the model. In order to establish these causal relationships, there needs to be an intervention on the value of the variables concerned, in this case relative phase (𝜙) and frequency (*b*/*a*).

For *b*/*a* to have a causal relationship with𝜙, it would need to be shown that:

(M) *b*/*a* causes 𝜙 if and only if there are background circumstances B such

that if some (single) intervention that changes the value of *b*/*a* (and no

other variable) were to occur in B, then 𝜙 would change.

Scholz & Kelso ([1989]) increased and decreased the frequency of queues which subjects were instructed to match the frequency of their oscillations to*.* This represents an intervention on to an intervention on *b/a*. The results were in line with the HKB model’s predictions, showing that when oscillation frequency is slow (*b/a* > 0.25) there are two stable attractors in both in-phase and anti-phase conditions. As frequency increases (*b/a =*< 0.25) the anti-phase attractor disappears, and the system is liable to fall towards the in-phase attractor.

This satisfies (M) so far. The coupling ratio, *b/a*, is intervened on by increasing or decreasing the frequency of oscillations. Interventions on the value of *b/a* result in regular changes in relative phase, 𝜙. Hence, the relationship from *b/a to* 𝜙 is a causal relationship. Under the scheme of Woodwardian interventionism, the relationship described by the HKB model between *b*/*a* to𝜙 appears to meet the criteria for being “difference-making” or causal. This example shows how the interventionist solution to the problem of causal relevance can be applied to nonmechanistic, dynamical models just as well as it can to mechanistic models.

4.4. Test case II: Dynamical field model

My second test case is the dynamical field model of infant perseverative reaching developed by Thelen et al ([2001]), and discussed also by Zednik ([2011]). Thelen et al ([2001]) model the reaching behaviours of infants in an A-not-B error task. The A-not-B error occurs when infants are induced to repeatedly reach for a desirable object (a toy) which is hidden in one of two locations – location A or location B. When the infant witnesses the toy being repeatedly hidden at A, they are prone to erroneously continue reaching for A even if in subsequent trials the toy is clearly shown being hidden under B (hence it is called the A-not-B error).

The model investigates the variables that can influence this tendency to reach for either A or B. The dynamical field model relates the values of variables at each point (*x*) on a field overlaid onto the task environment – for instance, *x*A and *x*B will be the locations on the field where the hiding spots A and B are located. Each location has an activation value (*u*) and when *u* reaches a critical value, reaching is likely to occur towards that location. Several variables play a role in determining how activation changes over time, as the model demonstrates:

Where activation level (*u*) of every point (*x*) on the field changes over time (*t*) as a function of the field’s previous activation (*u*), an input vector (*S*), a cooperativity parameter (*g*), and a temporal decay constant (). I will investigate the effect of *S* on *u*. *S* has, according to the model, some kind of effect on the value of *u* – what I aim to establish is whether or not interventions on *S* do in fact reveal a causal relationship with *u*.

According to Thelen et al ([2001]) there is considerable experimental evidence for the causal relationship from *S* to *u*. *S* represents several concurrent inputs – task, specific, and memory. Interventions on the task input such as changing the distinctiveness or desirability of the toy increases or decreases activation at the chosen location (*x*A or *x*B) (Diedrich, Highlands, Spahr, Thelen & Smith [2001]). Specific input can be intervened on by giving cues to reach (the experimenter tapping or gesturing to a particular location) which similarly influences *u* at that *x*A and *x*B (Smith & Thelen [2003]). The effect of memory input is that of these previous inputs, which continue to influence *u*.

Like the HKB model, I think that the dynamical field model of infant perseverative reaching is therefore also a good example of a dynamical model that can be treated in interventionist terms to establish causal relationships. The input variable is a cause of changes in the value of activation, and is a difference-maker to the outcomes of the system. Whether or not the infant reaches for A or B is controlled by inputs to *S*, and this relationship satisfies Woodward’s requirement (M). [[9]](#footnote-9)

1. Genuine Laws
   1. The genuine laws concern

The genuine laws concern regards the use of dynamical equations as laws of nature in a covering-law explanation, as proposed by Walmsley ([2008]). The core of this concern is the uncertainty around what constitutes a genuine law of nature. There is considerable disagreement over what makes a law a law, a criticism that has been directed at law-based explanations for decades (see for example Salmon [1984], [1989]). The nature of laws continues to be a live topic of debate and it suffices to say that there is no uncontroversial position on laws. As such, this makes it hard to see how dynamicists like Walmsley ([2008]) can state with any confidence what makes a dynamical equation a law, given the lack of reliable criteria to judge them by. There is simply no widely agreed upon framework for determining what kinds of generalisations should be accepted as laws (Kaplan [2015]).

Despite this disagreement, a common intuition within the literature on laws is that they ought to be exceptionless and universal in scope (Woodward [2003]; Kaplan [2015]), neither of which seem to apply to dynamical models. Dynamical models might apply to a wide range of phenomena, but they are not exceptionless – for instance, the HKB model does not apply to all examples of coordination such as gait switching from walking to running in humans.

In addition, it is debateable whether laws of nature are applicable within certain scientific domains. For instance, while laws of nature are not uncommon within physics and chemistry, they rarely figure in the explanations produced by biologists, neuroscientists and cognitive scientists (Woodward [2003]; Craver [2007]; Bechtel [2011]). This is coupled with an absence of laws in these domains: “uncontroversial examples of laws are less easy to find in sciences like biology and geology and harder still to find in the social and behavioural sciences.” (Woodward [2003], pp. 183). Appealing to laws, then, might not be suitable outside the “hard sciences” of chemistry and physics.

These uncertainties create a problem for advocates of covering-law explanations since they require nomic expectability (Salmon [1984]) - that the law can be expected to reliably describe a set of relations between variables. Both the D-N and I-S models which comprise the covering-law mode of explanation depend upon either determinate or highly probable relationships between variables, upon which deductive or inductive arguments can be made. In the case of accidental, non-lawful generalisations there can be no nomic expectability since there is no way of knowing whether the relations between variables it describes will continue to hold in that way. Certainty that a set of relationships is lawful (and as a result dependable and stable) is therefore very important for covering-law explanation.

The follow-up of the genuine laws concern regards the avenues dynamicists can possibly take to remedy the situation, granted the uncertainty surrounding laws. Kaplan ([2015]) claims that there are two equally undesirable paths open to dynamicists – either they can claim that dynamical equations are *ceteris paribus* laws, or they can attempt to produce some set of criteria for what a law of nature needs to be. The *ceteris paribus* option leads into another thicket of uncertainty (Woodward [2002]), and the latter option could be a very difficult and long-term task, in light of ongoing debate surrounding such a set of criteria for laws. According to Kaplan ([2015]), dynamicists are better off conceding that covering-law explanation is not viable at present.

* 1. Using invariance in place of laws

When mechanists claim that laws of nature are rarely encountered or applicable outside of physics and chemistry, I agree entirely. However, laws are not the only kind of explanation-worthy generalisation available for a dynamical mode of explanation. Woodward himself argues that lawfulness is the wrong criterion to gauge the explanatory value of a generalisation by. Instead of being concerned about how exceptionless, universal in scope (or some other criteria) a generalisation is, we should look for how invariant the generalisation is in showing how different variables causally relate to one another:

[…]generalizations in the special sciences can be used to explain, as long as they are invariant in the right way, whether or not they are regarded as laws*.* (Woodward [2003], pp. 183).

Whether a set of relationships are covered by a law of nature is not important. What matters is how invariant they are, and as a result how reliable they are for the purposes of describing stable and robust patterns of causal and counterfactual relations. Non-lawful generalisations directed towards psychological, biological, and cognitive phenomena (and any other phenomena within a ‘special science’) are not precluded from being explanatory so long as they are shown to be invariant.

At this point I am diverging from the covering-law view proposed by Walmsley ([2008]), derived directly from Hempel ([1965]), and at which much mechanist ire has been directed. Instead I propose that Walmsley, while generally correct in his assessment of the explanatory power of dynamical models, need not rely on a covering-law account (a direction of development he himself acknowledges). The covering-law account does, however, point us in the right direction in some respects:

In its emphasis on the role played by generalizations, including those taking a mathematical form, in explanation and causal analysis, the interventionist account has some affinities with the DN model. (Woodward [forthcoming] pp. 7)

So, the intuitions of dynamicists like Walmsley are more or less correct. Dynamical models provide useful generalisations, and show dependencies between antecedent facts and this generalisation – a valid approach under both the covering-law and interventionist approaches. Woodward however provides a less problematic alternative to laws of nature in the form of invariant generalisations. Instead of talking about laws of nature dynamicists can talk about invariant generalisations. The general form of dynamical explanation, in shifting from a covering-law to an interventionist approach, changes surprisingly little.

While Walmsley ([2008]) specifies a kind of explanation derived from antecedent facts and laws of nature, using dynamical equations in the place of laws, here I suggest that a more robust account of dynamical explanation would replace laws with invariant generalisations, and thereby entirely avoid the genuine laws concern. My goal is not to rule out the possibility of the existence of laws, or to argue that they have no role in providing explanations. Instead I am bracketing the issue entirely, and showing how according to the interventionist framework dynamical models can figure in explanatory accounts.

* 1. Test case I: The HKB model

We can start to form a picture of a mode of nonmechanistic explanation where dynamical equations are explanatorily useful based on their invariance, using the HKB model. The critical question is: can the HKB equation meet the requirements of invariance? An invariant generalisation fulfils two important criteria:

(i). The relationships described in the generalisation are causally efficacious or “difference-making”.

(ii). The generalisation is stable under a range of interventions.

The arguments presented in Section 4 already provide an answer to (i): the relationships described in the HKB model can be intervened upon to show how they are causally efficacious, and the model therefore meets this criterion.

An answer to (ii) requires us to determine how stable, under a range of interventions, these causal relationships are. If the model remains descriptive of bimanual coordination under a narrow range of conditions, then its explanatory ‘depth’ will be very limited. This latter criterion (ii) is a sliding scale, compared to the binary condition (i). How invariant a generalisation is depends upon the interests of the investigator – invariance is greater when the generalisation continues to hold over a greater range of values of variables we are interested in.

In the case of the HKB model, if our interests are in explaining bimanual coordination in humans, then the model ought to cover the range of values that humans are capable of. A sufficiently invariant generalisation ought to cover all the scenarios we will encounter when trying to explain this phenomenon, while a less invariant generalisation would only hold across a portion of them. For instance, if the HKB model only held in conditions of low frequency, where *b/a* > 0.25, then it would have a limited invariance.

In view of the experimental results, the HKB model appears to be stable across a sufficiently broad range of interventions – there is no observed frequency, high or low, at which the model ceases to describe the relationship between *b*/*a* and𝜙. For the purposes of empirical research on human subjects (i.e. Scholtz & Kelso [1987]) the model is stable. We could imagine circumstances where the model might break down – for instance if the frequency became too rapid for human subjects to maintain. However, invariance does not require universal scope, and admits of degrees. For the purposes of explaining bimanual coordination in humans, the HKB model appears to be sufficiently stable and hence invariant (Kaplan ([2015]) also discusses this scenario at length).

The dynamical equation at the heart of the HKB model qualifies as an invariant generalisation, fit for the purposes of explanation, filling a similar role to laws of nature in the covering-law mode of explanation. The relationship between *b*/*a* and 𝜙 described in the HKB model meets Woodward’s criteria for an invariant generalisation, and it is therefore explanatorily useful.

* 1. Test case II: Dynamical field model

Like the HKB model, the dynamical field model equation meets the criterion (i) for invariance – the target variable *S*, when intervened upon, reveals causal relationships between itself and the effect variable, *u*. The model describes the underlying causal structure of infant perseverative reaching and the A-not-B error.

The model can also meet criterion (ii), demonstrating sufficient stability to be an invariant generalisation and fit for explanation. The model is stable enough that constructing experimental scenarios based on the model across a wide variety of circumstances – even in extreme scenarios, like where no toy or cue from the experimenter is presented at all, representing a null value for the task and specific inputs elements of *S* (Thelen et al [2001]) – the model continues to accurately describe and predict the infant reaching behaviour (Smith & Thelen [2003]).

Under these kinds of circumstances that we might want to investigate in order to explain infant perseverative reaching, the dynamical field model remains stable under intervention. Hence, I think the dynamical field model is sufficiently stable to meet criterion (ii), and subsequently qualifies as an invariant generalisation.

1. Prediction
   1. Predictivism

The third criticism of dynamical explanation is what some mechanists have called *predictivism* (Kaplan & Craver [2011]), the position attributed to dynamicists who hold that prediction is sufficient as explanation. As we have seen, dynamicists like Chemero & Silberstein ([2008]) consider the predictive powers of dynamical modelling to be indicative of some deeper, explanatory power on the part of those dynamical models.

Mechanists have responded by pointing out the insufficiency of prediction for explanation. One frequently invoked example is that of a barometer (Salmon [1989]; Kaplan & Craver [2011]; Kaplan [2015]). A barometer, which measures air pressure, is excellent at predicting rainy weather. A sudden drop in air pressure is correlated with a change in the barometer’s readings, which is in turn correlated with imminent rain. However, it would be false to claim that as a result of these readings, the barometer is the cause of the rain, or that the barometer readings somehow explain the phenomenon of rain.

This criticism alleges that what dynamicists are doing is conflating prediction (which can be purely correlational) with genuine causal explanation. Hence claiming that the predictive powers of dynamical models make them explanatory is misguided, since there is no justification for suggesting that any amount of predictive power will grant explanatory power to a model.

* 1. Crude & invariant prediction

In their use of the barometer example, mechanists like Kaplan & Craver ([2011]) are referring to an example of what I will call crude prediction. Crude prediction refers to merely correlational, non-invariant relations between variables. A correlation exists between the barometer reading and the imminence of rain, where the reading is a useful predictor of rain, but there is no causal relationship at work between these two variables. This kind of crude prediction is rightly to be thought of as accidental and with little to no explanatory value.

I argue that another kind of prediction, which I will call invariant prediction, can provide explanatory power. While predictions made on the basis of correlations (like the barometer) are evidently not indicators of explanatory power, not all predictions are made on this basis. What I am pointing to here is a combination of counterfactual support and prediction, where a model is capable of showing what would happen if circumstances were different on the basis of an invariant generalisation.

Invariant prediction is made on the basis of the counterfactual-supporting abilities of an invariant generalisation – and these predictions are the kind of counterfactual dependencies that Woodward-style explanations are built on. Counterfactual dependency, as a point of clarification, is distinct from mere non-causal description in that it shows how one or more causal relationships connect to one another. It does this in a sense that is more than just establishing what is “barely true” by appealing to certain “truth-makers” like invariant generalisations. (Woodward [2008] pp. 230)

Crude prediction does not result from knowledge of invariant generalisations and as such is merely correlational and accidental. It is not indicative of explanatory power. Invariant prediction is conversely made on the basis of knowledge of the stable causal relations governing that system, and how that system will behave under a range of different counterfactual scenarios. If explanation is a matter of describing counterfactual-supporting invariant generalisations (Woodward [2003]), then the claim I am making here about invariant prediction and counterfactual support seem largely in line with this explanatory goal. A model which can provide invariant predictions based on the counterfactual dependencies it describes is an explanatory model.

For instance, the dynamical field model can predict the outcomes of infant perseverative reaching based on knowledge of the causal relationships between variables, within a sufficiently stable (and hence invariant) generalisation. Even without actually observing the outcomes associated with the input variable *S* holding a particular value, the invariance of the equation means that we can entertain the counterfactual, and predict what the outcome would have been. These predictions, based as they are on a sufficiently invariant generalisation, have the same kind of explanatory import as observations of particular outcomes. Whether or not the predicted result actually obtains or not is not significant: if made on the basis of an invariant generalisation then a prediction has explanatory power.

This approach to prediction and explanation comes close to resembling the covering-law mode of explanation, but without its attendant flaws – the causal relevance concern and the genuine laws concern – which should not trouble the present account since, as we have seen in Sections 4 and 5, it resolves them by integrating Woodward’s notions of ideal interventions and invariant generalisations.

1. Interventionist Criticism of the HKB Model

Recently, Woodward has been critical of the HKB model’s capacity to provide explanations. He argues that the HKB model is a “non-starter” (Woodward [forthcoming] pp. 23) for explanation, on the grounds that the model fails to associate itself sufficiently with features of the world, and is therefore not explanatory:

To the extent that the theory does not specify at all what structures or relations in the world are supposed to correspond to the dependency relationships postulated in the theory, then, according to the interventionist framework, it is not even a candidate for an explanatory theory. (Woodward [forthcoming], pp. 22).

Woodward’s requirement is something like a softer version of Kaplan & Craver’s ([2011]) 3M requirement, where there must be a direct mapping of variables in a model to components of the mechanism being modelled. This version is asking (without the explicitly mechanistic requirements) for some sort of association between features of the world and the model in question. The problem in its purest form seems to be this: a model cannot explain anything if the model is not clearly associated with an explanandum (features of the world). I take this to be a fairly uncontroversial claim about explanation – explanations need to be about something, or they are not explanations. If Woodward’s criticism hits the mark, then the HKB model is not sufficient as an explanation of bimanual coordination because it does not tell us enough about what features of the world the model is actually modelling, and hence what the explanandum actually consists in. It is potentially ‘[…] just a mathematical structure or an entirely uninterpreted set of equations relating certain variables’ (Woodward [forthcoming] pp. 22). By extension, this could cause trouble for the explanatory power of other dynamical models.

I think that this claim lacks force though, because Woodward’s mapping requirements are indistinct. What counts as sufficient grounding in features of the world seems very open to interpretation. For instance, Woodward thinks that while the HKB model is a non-starter for explanation, the dynamical model of the Hodgkin-Huxley model of the action potential is explanatory, because it associates itself with a physical system – it is about the neuronal action potential. However, I disagree that there is a significant difference between Woodward’s chosen case of the HH model, and the HKB model, or that Woodward has so far articulated some principled way to separate them. The HKB model is also about features of the world – it is about the physical system which exhibits bimanual coordination. When experimenters conduct research on the HKB model and bimanual coordination they are surely investigating some features of the world. The fact that experimentally testing the HKB model can be carried out at all seems to eliminate the possibility of the model being so vague about its constituents as to be a non-starter.

Lacking a good account of how to determine whether a model is actually associated with a particular system (outside the account of mechanistic explanation described in this paper, which does for appropriately mechanistic phenomena) is a problem for nonmechanistic accounts of explanation. However, the account I offer in this paper goes some way towards resolving this concern. Using interventionism in concert with dynamical models, we can establish the closeness of fit between a dynamical model and the causal structure of the features of the world it is modelling. The best models (and those that explain) will be those that describe that causal structure accurately according to an interventionist account. Development of the approach to dynamical explanation outlined in this paper may help further assuage this concern.

1. Dynamical Explanation

Mechanist criticisms of dynamical explanation are not fatal to the enterprise, and dynamical explanation is viable. By modifying the covering-law account proposed by Walmsley [(2008)] to instead resemble Woodward’s [(2003)] account of explanation, dynamical explanation can avoid potential problems of causal relevance, concerns about the status of dynamical equations as laws of nature, and the use of prediction as an indicator of predictive power.

So, what should an account of dynamical explanation look like? Firstly, dynamical models can provide causal explanations, so long as an ideal intervention can expose the causal relationships between variables featured in the dynamical equations featured in the model. In addition, the covering-laws proposed by Walmsley can be instead thought of as invariant generalisations, which operate in much the same way as laws of nature but without the requirements of being universal in scope or exceptionless. If dynamical equations meet Woodward’s requirements for invariance, they are suitable as invariant generalisations. A combination of dynamical equations and ideal interventions on the variables features in those equations is sufficient for explanation. These dynamical explanations also furnish invariant predictions of counterfactual scenarios, and these predictions contribute to explanatory power.

The HKB model and the dynamic field model provide exemplary cases of dynamical explanation. Firstly, ideal interventions on the variables at work in these models show how relative phase caused by the coupling ratio, and activation is caused by task inputs respectively. Secondly, these equations are useful as invariant generalisations, which possess sufficient stability and difference-making capacity to be used for the purposes of explanation. Finally, the ability of these models to predict counterfactual scenarios contribute to their explanatory power when coupled with the invariance of the equations.

1. Conclusion

My claim is that mechanist criticisms of dynamical explanation can be overcome by adopting an interventionist perspective on explanation, and applying it to dynamical models. I have shown how the causal relevance concern, the genuine laws concern and the charge of predictivism do not deflate dynamical explanation, and how dynamical models can meet the requirements of Woodward’s interventionist account of explanation. Once the account of dynamical explanation is adapted to rely on invariant generalisations and the broader Woodwardian account of explanation it avoids the problems mechanists have targeted. For mechanists to argue against the explanatory power of dynamical models under an interventionist framework, they would need to show either that dynamical models are for some reason not valid candidates for invariant generalisation, or that interventionism itself is flawed. This article shows that the former is not true – dynamical models can meet the criteria for invariant generalisations. The latter approach would be equally damaging for mechanistic explanations, since they also hinge upon interventionism. Through this defence I have also outlined an account of how dynamical models can apply the interventionist framework and demonstrate their explanatory power.

Acknowledgments

My heartfelt appreciation and thanks to Michael Kirchhoff, Dan Hutto, Patrick McGivern, Nick Brancazio, Miguel Segundo Ortin, Alan Jürgens and Anco Peeters for their feedback and encouragement in writing this manuscript. Many thanks also to two anonymous referees whose comments and recommendations were both generous and illuminating.

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1. Related arguments have been presented by Gervais & Weber ([2011]), Dupré ([2013]), Silberstein & Chemero ([2013]) and Woodward ([2013a]). In these cases, the specifics of how interventionism would be applied to dynamical models is left unsaid. Here I have attempted to greatly expand on these sketches and show in detail how interventionism can be integrated into an account of dynamical explanation. [↑](#footnote-ref-1)
2. While this paper focusses on dynamical modelling and dynamical explanation, the term “nonmechanistic explanation” refers to a diverse range of explanatory strategies including topological explanation (Huneman [2010]; Sporns [2011]; Stepp *et al.* [2011]), structural explanation (Hughes [1989a]; Bokulich [2011]) and functional explanation (Weiskopf [2011]). [↑](#footnote-ref-2)
3. Concerns about decomposition and localisation strategies may be conspicuous by their absence in this paper. The same dynamicist and mechanist camps are engaged in an ongoing (and closely related) debate about the necessity of these heuristics in explanation. Silberstein & Chemero ([201]3) for instance claim that some nonlinear and complex phenomena are best explained without low-level mechanistic detail, a view echoed by Woodward ([2013a]). Some mechanists (Bechtel & Abrahamsen [2010], [2013]; Craver & Kaplan [2011]; Kaplan & Craver [2011]; Kaplan [2015]) by contrast argue that decomposition and localisation are vital for genuine explanation, and that dynamical models only explain when they incorporate mechanistic details. I bracket this issue here, since my focus is on the interplay of interventionism and dynamical explanation, not the necessity of mechanistic detail for explanation. [↑](#footnote-ref-3)
4. For an overview of the recurring problems with several other (now historical) accounts of causal relevance, see Craver ([2007]). [↑](#footnote-ref-4)
5. Those who do not subscribe to counterfactual explanation or interventionism may already have different views on nonmechanistic explanation. However, my targets are specifically those mechanists who do uphold Woodwardian interventionism. [↑](#footnote-ref-5)
6. Craver ([2007]) extends this counterfactual account by also specifying that a mutually manipulable, inter-level constitutive relationship must hold between the mechanism and the explanandum phenomenon. The scope of this article, however, only covers the causal and counterfactual side of mechanistic explanation and its relationship with interventionism. [↑](#footnote-ref-6)
7. Though the nature of the distinction between description and explanation is contentious, the existence of a distinction is generally accepted. Advocates of both mechanistic (Craver & Kaplan [2011]; Kaplan & Bechtel [2011]; Kaplan & Craver [2011]) and dynamical approaches (Chemero & Silberstein [2008]; Silberstein & Chemero [2013]) agree that there is a difference between mere description and explanation of a phenomenon. [↑](#footnote-ref-7)
8. Another related question is the possibility of macro-to-micro level causation (Baumgartner 2009, 2010; Baumgartner & Gebharter 2015). In the case of HKB, this would mean that *b*/*a* and𝜙, being macro-level variables of the dynamical system that they supervene on, are not capable of causation independent of their micro-level supervenience base. If one cannot intervene on 𝜙 without also simultaneously intervening on the micro details which form the supervenience base for 𝜙, then supposedly there cannot be causation from the macro-level down to the micro-level. Woodward ([2015]) offers a solution by adding a clause to his requirements for interventions specifying that non-causal relations (like constitutive or supervenience relations) do not need to be controlled for during interventions on macro variables, which means macro variables are not prone to systematic overdetermination of effects or becoming epiphenomena. While Baumgartner & Gebharter ([2015]) argue that this adjustment undermines Craver’s account of constitutive relationships (and take this as a motive to find an alternative) my purpose here is not to defend mechanistic explanation, and hence whatever violence is done to mechanistic constitution relations is not for me a good reason to reject Woodward’s amendments. [↑](#footnote-ref-8)
9. (M) also requires that the relationship be between *b/a* to 𝜙 and excluding other confounding variables. This is a sensible requirement since we would like to know that *b/a* is the cause of𝜙, and not some other hidden variable or a combination of *b/a* and some other variable. Much like for non-dynamical or mechanistic models, identifying and controlling for confounding variables is done on a case-by-case basis, with a view to (at least) conceptually disentangling confounding variables and controlling for them (Woodward [2003]). In the case of the dynamical field model, it would be important, per Woodward ([2003]), to correct for the influence of (for example) the cooperativity input g when determining the causal role of *S* on *u*. While in practice it may be impossible to set up a scenario where *g* does not also influence *u*, we only need to be able to imagine an ideal scenario where the influence of *g* was removed. [↑](#footnote-ref-9)