The Conductome – A Conceptual Model

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1) Introduction

Every major problem that humankind faces can be linked to the consequences of human *behaviour*. As well as obesity, chronic and other lifestyle diseases - addictions, loss of biodiversity, climate change, pollution, violent conflict, fake news and others, all arise from how we *conduct* ourselves in our decision making, at both the individual and collective levels.

The universality of these global problems, that are a direct result of our behaviour, demonstrates that underpinning these problems there exist, despite its complexity and richness, quite universal tendencies in human behaviour that are produced by biases that orient us to act in certain fixed directions, often with adverse consequences. Although many of these biases have a biological, and, consequentially, an evolutionary basis [1], they are also subject to modulation by interaction with the environment. In other words, some behaviour is changeable. Indeed, recognising and quantifying the degree of plasticity of a given adverse behaviour is an important prerequisite for ameliorating its impact.

It is important to recognise that only Complex Adaptive Systems (read - living systems) exhibit behaviour, conduct themselves and make decisions. Complexity is manifest in the immense multifactoriality of individual decisions themselves, which depend on a multitude of different factors, ranging from our genetic and epigenetic beginnings to the influence of an entire life history of interaction with a constantly changing social, psychological, economic and political environment. On the other hand, adaptability is associated with the fact that decisions and behaviours can change according to both the internal state of the decision maker and the state of the environment.

The highly multifactorial, adaptive nature of decision-making has meant, until recently, the impossibility of adopting a more data-driven approach, due to the difficulties of obtaining the relevant data across a host of different scales, associated with multiple disciplines and multiple experimental protocols, that could begin to represent the gamut of factors that influence our decisions. A systemic, transdisciplinary understanding of human behaviour is impossible without the integration of such multi-scale, and therefore multi-disciplinary, data.

Decision-making then can only be understood from a truly systemic point of view. Such systemic approaches have been gradually adopted in fields such as systems biology, where it has been recognised that a systems-based, integrative approach is necessary in order to understand, for instance, collective behaviour at the cellular level. These more integrative approaches have been associated with the concept of an "ome" – metabolome, proteome, genome, transcriptome etc. – where the totality of factors within a given data type is considered [2]. Most "omes", however, look principally at the molecular level. Genomes, epigenomes, proteomes, transcriptomes and metabolomes are all examples where the goal is to characterize the full set of molecular components and their interactions for a given ome. So, the "ome" concept is associated with trying to look at the totality of factors associated with a given system but, importantly, viewed from a certain perspective – the "micro" – where the structures that participate, and their interactions, are at the molecular level.[1]

Other omes have been suggested, such as the infectome [3], or the physiolome [4]. These also, however, though not being necessarily at the molecular level, are restricted to a certain scale – such as the scale of organs and tissues in the case of the physiolome. Of course, one must ask - what are the advantages of such an omic perspective? One important advantage is that such an approach is much less reductionist than non-omic perspectives. However, although an omic viewpoint is certainly more integrative than a non-omic one, the current omes are, as mentioned, scale restricted, in that they consider system components at a particular scale.

Taking a "totality of factors" interpretation of an ome, in this chapter we will discuss the concept of a Conduct-"ome", as being the appropriate framework in which to study human behaviour. Moreover, as we will see, as conduct is intimately related to the notion of *prediction*, we will frame our discussion of conduct in the context of probabilistic prediction models, $P(C|\mathbf{X})$, for a given conduct C conditioned on the totality of factors, $\mathbf{X}$, that affect it. This requires an integration of phenomenological elements that extend far beyond the micro-realm of bioinformatics, requiring a multi-scale approach that includes not only genetic and epigenetic elements, but, also psychological, neurological, social, physiological, clinical, socio-economic, socio-demographic, socio-political and philosophical elements, among others.

Although the Conductome is a general concept, applicable to any conduct and its potential association with a given problem – climate change, obesity, violence etc. as the emphasis of this book is on obesity, we will construct a theoretical framework in which to analyse and test the Conductome that uses obesity as a relevant context. In particular, we will propose a mathematical framework that is Bayesian in nature and construct an explicit example of a Conductome, associated with a particular conduct – C = "sedentariness" – that is a relevant risk factor for the development of overweightedness and obesity and, subsequently, metabolic disorders, such as type 2 diabetes.

Although we will emphasize the Conductome in the context of obesity, it is necessary to first develop a theoretical framework in which to frame the discussion. Thus, the structure of the chapter will be as follows: we will first discuss in section 2 "what is behaviour?" In section 3,

[1] Interestingly, physics, implicitly, has always taken such an omic approach. The complete set of components of fundamental matter and their corresponding interactions have been fully characterised and we know a great deal about how different structural levels of matter – nuclei, atoms, molecules etc. emerge from these components. As with the biological "omes", however, the physical "omes" are restricted to a given scale.

we argue that behaviour and conduct can only be properly understood from a probabilistic perspective and as a problem in statistical inference. We therefore lay out the foundations of a formal, probabilistic framework within which decision making and conduct may be better understood. In section 4 we further explore the development of a mathematical framework in which decisions and decision-making can be better understood centred on the notion of $P(D \mid \mathbf{X})$, the probability of a decision D conditioned on a set of factors, **X**, that influence it, while in section 5 we consider a pictorial representation of this probability – the Decision Landscape. In section 6 we introduce the Conductome itself using sedentariness as a use case and in section 7 draw some conclusions.

2) What is behaviour?

Given that we are concerned with behaviour and conduct it is pertinent to first ask: What is behaviour? We cannot, of course, provide a comprehensive review here of the subject matter associated with answering this question. We will, rather, introduce only what is necessary to develop our narrative. There is no definition of behaviour accepted universally across multiple disciplines. However, a common and representative characterization in biology is that [5]:

"**behaviour** is the internally coordinated response (actions or inactions) of whole living organisms (individuals or groups) to internal and/or external stimuli."

While the definition to be found in the dictionary of the American Psychological Association [6] posits

"**behaviour** is an organism's activities in response to external or internal stimuli, including objectively observable activities, introspectively observable activities and nonconscious processes."

From both perspectives, behaviour is considered to be an association between a *cause* (internal/external stimuli) and an *effect* (response - action or inaction). The question then is: just which causes, effects and cause-effect relations may be considered behaviours? First, what is an "effect"? How would we characterise it? We consider an effect to be a change in the *state* of a system, which we will denote as the "subject", **S**, and is a crucial component in the description of any system. A state, $\mathbf{X}(\mathbf{S},t) = (X_1(\mathbf{S},t), X_2(\mathbf{S},t),\ldots, X_N(\mathbf{S},t))$, may, in principle, be specified using a set of state variables $(X_1, X_2,\ldots, X_N)$. An effect can then be defined as a change in the state of the system, such that $\mathbf{X}(\mathbf{S}, t) \rightarrow \mathbf{X}(\mathbf{S}, t+1)$.

It is a most important and fortunate fact that the states of non-living systems can generally be described using a small set of relevant state variables and/or labels and, in this way, we may delineate all possible states of a system – which we call the *state space*. For example, from a mechanical perspective, the centre of gravity of a system, and its coordinates $\mathbf{X}(\mathbf{S}, t) = (X(\mathbf{S},t), Y(\mathbf{S},t), Z(\mathbf{S},t))$, is an important descriptor of an object; one that can be equally applied to both living and non-living systems. However, living systems are associated with an almost limitless set of other potential state variables, that extend from the micro, sub-cellular level, to the macro, whole organism level, and beyond, to the group level.

For example, beyond the position of their centre of gravity, how might we describe the state of a person? Happy/sad, male/female, old/young, hungry/satiated, sitting/standing, fat/thin, hispanic/caucasian, big/small, heart beating fast/slow, diabetic/non-diabetic etc? Furthermore, in physical systems we can arrive at a quite satisfactory description of its state, using only a few variables, whereas in living systems we have no a priori fixed, limited set of relevant state variables that offer a "complete" description, at least for an interesting subset of phenomena associated with a particular scale. Additionally, in distinction to non-living systems, in living systems, we have little to no idea, even conceptually, as to how to map an organism's macrostates to microscopic physical variables.

Of particular interest is how a state changes over time. For example, how normal weight becomes overweight, how hungry becomes satiated and how physically active becomes sedentary. States change according to a state update rule, F_c, that tells us how the state $\mathbf{X}(\mathbf{S}, t)$ changes into a new state $\mathbf{X}(\mathbf{S}, t+1) = F_c(\mathbf{X}(\mathbf{S}, t))$ at a later time, t+1, due to the presence of a "cause" c. This state change can be mapped into an action, **A**, such that $A = A(\mathbf{X}(\mathbf{S}, t+1), \mathbf{X}(\mathbf{S}, t))$, the action A being that which engenders the change of state. As an example, consider the centre of gravity coordinates as a partial description of a person. If we had that information, we could deduce an immense amount about the behaviour of that person: where they eat, when they eat, if they exercise, whether they take the stairs versus the elevator, *ad infinitum*. Of course, in order to do this, we need to have *knowledge* about the different places where they spend time. For example: is it a gym or a restaurant?

For physical systems, generally, there is only one relevant update rule for $\mathbf{X}(\mathbf{S}, t)$ – think of falling from a tree, where Newton's universal law of gravitation is the only update rule that is relevant for your centre of gravity! This update rule, however, would not tell us anything about the accelerated heartbeat that you would experience, or whether you screamed in fear. Newton's law is *universal*, meaning that everyone and everything is equally subject to it. It acts on our centre of gravity in the same way. Energy conservation is also universal, and this is a fundamental starting point for considering the role of energy imbalance in obesity. In principle, if we could fully understand the complex physiology of energy conversion, we could predict how much weight, considered as a state variable, a person would gain after eating a certain food, considered as a cause.

In contrast, think of the update rule for $\mathbf{X}(\mathbf{S}, t)$ that governs who will exercise today or what and where they will eat. What could be some relevant state variables? The position of the person is one possibility, of course. However, there is no analogue of the Law of Gravity that determines where we will eat! The most appropriate framework in this case is akin to game theory [7], such as in Tic-Tac-Toe or chess, where a choice of different update rules is possible, with the update rule in that case being identified with a "strategy", with each strategy being associated with a decision rule that can lead to different outcomes. Of course, we may ask: How does one arrive at a given update rule? The Theory of Planned Behaviour [8] is one area that is concerned with this question. From the point of view of complexity, an important question is: What does my update rule depend on? This will usually depend on a large number of factors. For instance, in the case of whether a person will exercise or not, if their position is far removed from the position (coordinates) of the place where they exercise, then this may be a cause as to why they do not exercise. On the contrary, if they are close, this can be a cause that leads to exercise. Whether they will or won't exercise, as we will see below, can also depend on their occupations, their economic situation, their past habits, their family and friends' habits, and a host of other factors. At the level of the individual, it can also change from one moment to the next, depending on whether you are tired or not; whether you are late leaving from work or not; if you can find a parking place, and many others.

We will take then a behaviour to be associated with *choices* among multiple update rules that change the state of a subject. In non-living systems, we claim that there is only one response, one update rule, that effectively governs the link between cause and effect, whereas in living systems there is more than one potential response.

a) **The difference between behaviour and conduct**

Why do we use Conductome and not Behaviour-ome? To answer this, consider a behaviour – eating. We can observe that there are associated patterns: when we eat, where we eat and what we eat. However, there is a "why" associated with this action, and this "why" is not explicitly present in the above definition of behaviour. To account for this "why" we prefer to use the word *conduct* rather than behaviour, as its etymology (https://www.etymonline.com/word/conduct) "to guide, accompany and show the way" captures the idea that there is a reason "why" stimulus and action are linked. Of course, this guide that "accompanies" us and "shows the way" is, indeed, evolution, in all its forms. Thus, when ghrelin levels are high (cause-stimulus) we may search for food (effect-action), with the cause-effect pair constituting the behaviour [9]. However, it is the evolutionary pressure from natural selection that has gradually guided individuals to search for food when hungry that provides the "why" behind this universal behaviour. It is evolution that allows us to interpret a behaviour as a conduct, and it is through conduct that evolution principally works, both at the genetic and cultural levels. It is also through conduct that an organism interacts with its environment, and it is changes in conduct that are either themselves adaptive or engendered by those structural adaptations in the organism that lead to observable changes in behaviour, i.e., changes in the observed effect given a certain cause.

From a human perspective, if we think of behaviours as being the actions a person demonstrates, then conduct can be thought of as the relationship between the action and the normative environment in which the behaviour is exercised. This normativity can be biological in nature – eating, reproduction etc. – or cultural, where, for example, a particular behaviour might be acceptable in one culture but not in another. Of course, the complexity of human conduct is enormous, as is manifest in the almost limitless number of different behaviours available to humans, both as individuals and as a species. However, there are certain behaviours that are fundamental and are in common with other organisms [10]. In particular, those that have their roots in survival, such as feeding, reproduction, evading threats etc.

As a biological species then, conduct is everything. Beyond the biological, as emphasized, human conduct is at the heart of the vast majority of social and health problems that we face, with obesity clearly being overwhelmingly a behavioural/conductual problem, with the relevant behaviours being overconsumption and sedentariness that, in their turn, lead to energy imbalance. When such problems are viewed from a behavioural standpoint, we tend to speak of behaviour change [11]. However, without a more thorough understanding of *why* a certain behaviour is exhibited it is impossible to predict how easily it may be changed, as we have no idea about the normative restrictions that our biological and cultural evolution have imposed. Thus, it is more appropriate to speak of conduct change as this accounts for the fact that we must distinguish between individual and normative environment and must understand the why behind the behaviour.

3) Behaviour and conduct as statistical inference problems

Behaviour according to the above definition is the link between a cause (external/internal stimuli) and an effect (internally coordinated response). In principle, this can be modelled mathematically as a change of state of a subject **S** due to a cause c: $\mathbf{X}(\mathbf{S}, t) \rightarrow \mathbf{X}(\mathbf{S}, t+1) = F_c(\mathbf{X}(\mathbf{S}, t))$. We have also argued that for this cause-effect relation to be characterizable as a behaviour, it should be associated with the presence of multiple potential update rules for the state of a system. We have also argued that only living systems exhibit multiple update rules [12]. Unfortunately, we have no *a priori* knowledge of F_c and, in many cases, we do not even have knowledge of the cause of an observed state change. Indeed, F_c and c itself must be inferred from observations. How is this inference process to be achieved?

Imagine seeing two people presented with a litre of Coca-Cola: One drank it and the other didn't. Would that be sufficient evidence to conclude that each person *behaved* so that if presented with a litre bottle of Coca-Cola one person *always* drank it and the other *never*? Additionally, how would we identify or infer the cause of the behaviour? What if the first person hadn't drunk anything for two days but hated Coca-Cola versus loved it? What if the second person was thirsty but diabetic versus had just already consumed a litre of Pepsi-Cola? There are many actions where the stimulus that caused it is not clear. Imagine seeing a man jog by you at 7am each day for a month. The hypothesis: "The man jogs at 7am every day", which has "the man" as subject, **S**, along with an **action**, A – "jogging at 7am" - would certainly be taken by most as an example of a behaviour; a healthy one at that. However, there is no overt linking stimulus in that sentence. Rather, any potential stimuli are implicit, or covert. Without a specific hypothetical stimulus, we are left to posit that there may be many reasons (causes) as to why the man jogs at 7am each day. There may also have been many alternative activities (actions) for the man at that time too, not the least of which is the non-action, or inaction, such that the man did not jog by at 7am. In these cases, the notion of decision enters, as we assume that the man *chose* to jog by at 7am as opposed to other activities, all of which can be subsumed into the category "did not jog by at 7am".

Imagine, however, on the first day: if you saw the man jogging at 7am, would that be sufficient reason to call it a behaviour? We would argue no, because behind the notions of behaviour and conduct is the notion of correlation, or tendency, particularly in time, as in a random world there would be no notion of either. Implicit then in our idea of behaviour is the idea of a statistical ensemble, either explicit or implicit. The explicit version would be an ensemble of observations that allowed us to construct a frequentist model of how likely it would be that we saw the man jogging on a given day. In other words, we could count how many times we saw the man jogging at 7am, N(*man seen jogging at 7am*), and the total number of observations, N, to compute the probability of seeing the man jogging at 7am as P(*man seen jogging at 7am*) = N(*man seen jogging at 7am*)/N. What then is N? Again, there are many ensembles that could be chosen. One could naturally only look for the jogger each day at 7am. In that case, N would be N = N(*man seen jogging at 7am*) + N(*man not seen jogging at 7am*) and therefore P(*man seen jogging at 7am*) would simply be the fraction of days in which the man was seen jogging at that time. In this case our observations are restricted to the time – 7am. The question then is: how many days do we consider? For only one day, if we see the man jogging at 7am, then N(*man seen jogging at 7am*) = N = 1 and therefore P(*man seen jogging at 7am*) = 1. Just as in coin-flipping, however, seeing a heads from one flip of the coin is not a sufficient basis for concluding that P(*heads*) = 1. Rather, we need to test our observation with respect to a null hypothesis, as will be discussed below.

The question of the choice of explicit ensemble is also intimately linked to the information that we use to specify an event in the first place. We could, for example, consider events whereby the man is seen jogging at some time, but the precise time is not an element in our specification of the event; or we could consider observations on the hour every hour. In the first case, the events of interest are seeing a man jogging at some time in the day, but with no interest in a particular time. Each day can then contain one and only one event. In the second case, however, there are 24 potential events where the man could have been seen jogging. Finally, we must acknowledge that an explicit ensemble may be constructed by different observers, including the subject themselves.

a) Internal versus external ensembles

In the above, we have taken a standard scientific approach to potentially characterising behaviours probabilistically, using the frequentist perspective of probabilities. However, we may ask: is that how humans or other organisms recognise and quantify behaviour? There is ample evidence to suggest that this is not the case, the existence of certain cognitive biases in the case of human decision-making being a case in point [1]. It is clear that Bayesian probability [13-19] is a much more adequate framework for understanding how organisms recognise and quantify behaviour, whereby a probability represents a belief or plausibility rather than an empirically determined frequency. Moreover, in particular, Bayes theorem offers a natural framework in which probabilities may be updated in the light of new information.

In the case of the jogging man, if we think of this in Bayesian terms, we start with a prior probability, whereby having seen the man jogging by once we assign a probability, P(A), to whether we would see him jogging at 7am the next day, where now A represents the action – jogs by at 7am. However, after 30 days of seeing the man jog by at 7am, the posterior probability, P(A|X), where X is the information that on the previous 30 days the man jogged by at 7am, would be high, corresponding to the fact that we believed that the chance that we would see him jog by on day 31 would be much higher.

Of course, the statistical ensembles with which we will characterise behaviours may also be implicit. For example, I do not have to observe 30 diabetics in order to assign a high probability to the fact that they will not drink a litre of Coca-Cola. I have an implicit statistical ensemble in my mental model of diabetics and Coca-Cola that maybe constructed partially from personal experience, but also is constructed from reading about the subject or learning about it from others. If, however, I noticed in multiple subsequent occasions diabetics drinking litres of Coca-Cola I might well revise my mental model. We can thus speak of **internal** ensembles, that are implicit in our mental models, and which are based on Bayesian plausibility, as distinct to **external** ensembles, whereby behaviours are characterised purely empirically via event counting in a frequentist perspective.

In principle, with an appropriate external ensemble, we may characterize and quantify objectively a certain behaviour. However, with respect to an internal ensemble, the concept of behaviour becomes more subjective, whereupon the perceived plausibility of a given behaviour based on an internal ensemble could be very different from that which would be calculated from an objective external ensemble. Indeed, this difference is at the very heart of why we make so many decisions that have adverse effects. Of course, elements of the external ensemble can influence our internal ensemble and its associated probabilities and vice versa. That is, of course, how learning works, although this learning can be quite sub-optimal. Indeed, this is precisely why behaviour change is so difficult, that evidence from external ensembles is not correctly incorporated into our internal models.

The crucial point here is that behaviours can only be identified probabilistically. In terms of an external ensemble, we must therefore characterize behaviour and conduct via a set of observations of effects and their potential causes, with the set forming a statistical ensemble on which we will perform a process of statistical inference. Involved in this process are **Actions**, as effects, which are the result of **decisions**, D, where the concept of decision here is just another way of saying that there are multiple potential update rules, with the decision being identified with the choice of update rule used, given that there are several, even if it as simple as action/no action. Intuitively, from a cause-effect perspective, the statistical inference process is such that, for an ensemble of observations of a cause and its potential effects, when presented with similar circumstances, a person tends to make the same decision and perform the same action. In other words, we expect P(*effect* | *potential cause present*) > P(*effect*) or P(*effect* | *potential cause present*) > P(*effect* |*potential cause absent*). Of course, any such decision/action pair will have an outcome and that outcome may feedback through reinforcement learning into the conduct, to either reinforce it, in the case of a positive outcome, or change it, in the case of a negative one.

b) A first pass at a statistical framework for Behaviour and Conduct

Taking a purely phenomenological approach, as a first approximation to the characterization of behaviour and conduct probabilistically, we can characterize the relation between a stimulus/cause, *X*, and an action, *A*, to be characterizable as a behaviour if $D_1 = (P(A|X) - P(A)) > U$, where $P(A|X)$ is the probability that the action is observed, given the stimulus X, and P(A) is the probability of observing the action independently of whether the stimulus is present or not, while *U* is some to be defined threshold. This captures the idea that a person is more likely to exhibit the action A in the presence of the stimulus *X*. Of course, we could also consider $D_2 = (P(A|X) - P(A|\bar{X})) > U$, where now, $\bar{X}$ represents the absence of the stimulus. The two measures just use two different benchmarks for measuring the tendency associated with the behaviour: D_1 comparing the probability for observing the action given the stimulus, relative to seeing the action independently of whether the stimulus is present or not, while D_2 compares the probability of observing the action in the presence of the stimulus relative to the probability of observing it in its absence. In both these cases we may use either an external or internal ensemble to quantify the probabilities.

The existence of a reference point with which to compare *P(A|X*), and thereby quantify it, is essential for the characterization of a behaviour. The probabilities $P(A|X)$ can be thought of from a Bayesian perspective or a frequentist perspective, where, in the latter, if we have a defined external ensemble of observations, we may calculate $P(C|X) = N(CX)/N(X)$, with $N(X)$ being the number of times the stimulus is observed and $N(CX)$ the number of times the action is observed "concurrently" with the stimulus. This notion of concurrence is subtle, and we will return to it.

Given a statistical ensemble of observations we may consider the statistical significance of the difference between the observed probability of the stimulus-action and the corresponding benchmark – now a null hypothesis. We can do this with a statistical test, such as a binomial test [20]. In the case that the binomial distribution can be approximated by a normal distribution then $|\varepsilon(A|X)| > 1.96$ would correspond to the standard 95% confidence interval that the observed relation between the stimulus and action is not consistent with the null hypothesis. In these terms a reflex action, such as jerking your knee (A) when hit by a doctor's hammer (X), would effectively have $P(A|X) \sim 1$. Similarly, addictions that link addictive stimuli and their corresponding actions would have high conditional probabilities, while strong aversions would have $P(A|X) \sim 0$. Operant conditioning would be such that $P(A|X)$ changes in response to the reward from the action A, increasing/decreasing with positive/negative reinforcement [21].

So, how would we apply this formalism to a person and their behaviour in the presence of a given food item, such as a sugary doughnut? The first complication is deciding just what our external statistical ensemble should be. For example, for the *action = person eats doughnut*, imagine that we have a set of N observations, such that P(*person eats doughnut* | *doughnut present*) = 1. What is the appropriate null hypothesis? Naively we cannot consider P(*person eats doughnut* | *doughnut absent*) as this is a tautology. The person can't eat a doughnut that isn't there. We could, however, consider a larger ensemble, consisting of various persons where, for instance, we find that over that ensemble P(*person eats doughnut* | *doughnut present*) = 0.2. We can then compare the probability that a person in particular eats the doughnut versus the group.

Of course, we do not need to construct a carefully controlled scientific experiment to count the number of times that a person has a certain "internally coordinated" response to an external doughnut stimulus and that that response is such that for a given person the probability that they eat the doughnut is significantly greater than that of the typical person. How so? Because we have an internally generated mental ensemble of person actions and doughnut stimuli. In this case, besides regarding $P(A|X)$ as representing a statistical relation between A and X based on observation, it can also be considered to be a prediction model, where on observing the stimulus X we **predict** that the action A will be observed with probability/plausibility $P(A|X)$. This will be an important point when we come to trying to understand the predictive drivers of those decisions that have adverse outcomes, as well as trying to understand the degree of plasticity of the driver.

There are two important caveats to this simplified approach, however: one is that the outcome A will depend on many more factors than the pure presence of the stimulus X (would that the world were so simple!). Our action on being presented with a doughnut would be quite different in the circumstance that we had not eaten in two days versus we had already just consumed a full meal. Thus, in reality, we must consider the relation between an action and the complete set of state variables that could affect the relation between cause and effect. The second caveat is that, here, we are considering the action from a binary standpoint, i.e., that A occurs, or it doesn't. However, if there are a range of possible actions, $A_1, A_2, \ldots,$ then $P(A_i|X)$ tells us nothing about the individual probabilities $P(A_j|X)$ and just refers to A_i or *not* A_i.

What happens though in the case where the stimulus-cause is not recognised, or apparent, such as in the case of our jogger? In this case we have the probability of the action, P(*jogs by at 7am*). What then is our ensemble? There are different possibilities. One would be just the set of observations – man jogs by at 7am – yes or no? There is a subtle point though about how we generate our ensemble. The man jogs by between 6.55am and 7.05am considering all days? The man jogs by between 6.55am and 7.05am considering only weekdays (because that's the only time you can make the observation)? The man jogs by between 7am and 7am and 3 seconds? Each one of these may lead to a different estimate according to how we characterise the notion of concurrence of events in space and time. We are not aware of the precise way in which we construct our mental model ensembles in situations such as this, but the fact remains that we do. As, indeed, to one degree or another, all organisms do.

c) A second pass at a statistical framework for Behaviour and Conduct

In the previous section we have argued that behaviour and conduct need to be understood probabilistically and that therefore we need to construct a statistical ensemble. We will now attempt to construct more formally such an ensemble by defining those elementary events or interactions that will compose it. In other words, behaviours/conducts will be composed of correlated sets of suitably defined elementary events.

In fact, the appropriate elementary events are decisions, as we will argue below. However, we will first form an ensemble by defining as elementary events – **interactions**, I(S,O,A) – a combination of subject, S, action, A, and object, O, that represents an unique, discrete event in space and time. For the moment we will consider this to be an external ensemble. The subject will be that thing/person that carries out the action (or not), while the object will be that thing/person to which the action is directed. Note that actions do not always necessarily have an object *per se*, just as in language a sentence does not necessarily have an object. We will take the action to be that which is done, or not done, by a subject to an object, or which just changes the state of the subject or object. It is intimately linked to the concept of a verb in language, where the action corresponding to the verb can be considered as being planned, in process, or completed.

Given the statistical nature of the characterization of behaviour, we may imagine the probability P(I(S,O,A)) that an interaction occurs. In this case, if S, O and A are the characteristics of that unique event, i.e., the definite article sense of S, O and A, then P cannot be interpreted in a frequentist sense, but must be interpreted in a Bayesian sense, i.e., it represents a belief or plausibility.

The action (update rule) in the interaction is chosen from a set of possibilities, with the choice being a decision process, where we will take a decision, D, to be associated with a subject, S, **planning**, **initiating** or **completing** an action, A, chosen from a set of possible alternative actions (update rules), {A}, and where the action often acts upon an object**,** O. We distinguish the notion of interaction from that of a decision in that in the former we will not necessarily take into account the existence of multiple possible choices of action in a given situation. A key point here is that, although we may objectively observe the correlation between a subject, object and action, the decision-making process itself is associated with the subject and not necessarily open to observation. Indeed, the decision-making process is more often than not quite opaque, even to the decision makers themselves.

Both actions and decisions can be intuitively characterised in the context of the 5 Ws: Who? What? Where? When? and Why? The Who? and What? are necessary for specifying the subject, object and action. The Where? and When? are necessary for understanding the spatio-temporal context of the decision/action, and the Why? is important for understanding the reasoning behind the decision/action. It is this latter point that will differentiate between behaviour and conduct. We may also add one “H” to the 5Ws, representing the “How” of the decision/action – what were the physical/chemical/neuropsychological/biological mechanisms by which the decision was made, and the action taken?

4) A mathematical representation of decisions

a) What then is a decision?

As mentioned, moving beyond the idea of an interaction, where the concept of decision enters is that for a given subject and object there are multiple actions, $\{A_k\}$, that could occur. At the minimum, we may consider whether a particular action occurred versus if it did not occur, where, for the latter, there might have been many other actions that might have occurred.

i) The space of possibilities for a decision

How we partition the space of possible actions is a subtle point. If we partition it into “option A” or “not option A” then it is relatively unambiguous. However, if we consider the “man jogging by at 7am” example, how do we decide if or not, besides “jogged by at 7am” or “didn´t jog by at 7am”, we should include: jogged by while dancing, or singing, or crying etc. as possible actions? Of course, intuitively, these might have very low probabilities. However, the question of how to denote and enumerate alternatives is at the very heart of what a decision means. In the case of the **real** world, in any given situation, it is likely that a certain subset of actions stands out as being the relevant one. However, just the notion of: “I didn’t expect them to do that!” shows the subtleties of characterising the possibilities. The problem is even more acute in the **virtual** world of an internal ensemble, where the circumstances that would suppress the probabilities of many actions are not present. A further point is the feasibility of an action. The space of possibilities will be strongly affected by a host of restrictions – physical, economic and social, to name but three types.

ii) Simple versus composite decisions and actions

To try and understand the complexity of what we might think of as an elementary decision let’s consider the decision and associated action to “eat a taco”. Although this action sounds simple, it is anything but, as it involves a large number of more atomic decisions and actions - most being associated with motor actions. Firstly, to eat the taco one must put oneself in the physical vicinity of the taco (decision – approach; action – step) so as to be able to reach out with an arm (decision – pick up taco; action – reach out arm and grasp taco in hand) then bring the taco to the mouth (decision – eat taco; action – bring taco to mouth); one must then open the mouth, manoeuvre a part of the taco into the mouth, bite down and start chewing and then swallow – and that’s all just the first bite! One then continues this procedure, potentially pausing between bites to chat, look at the scenery etc. The decision to take a second bite is a decision that is correlated to the first but does not follow a priori. Indeed, this is an example of a **conduct** – a series of correlated decisions and corresponding actions with an associated why. Furthermore, we may ask to what degree these decisions are under control from different parts of the brain.

The key point here is that the decision and action “eat the taco” is really a compound action that involves a large number of other decisions and actions. In fact, the vast majority of familiar actions are really compound actions. Walking, talking, eating, playing football, watching television, listening etc. are all composed of a large number of other actions, many of which may even be involuntary. We are listening and seeing and acting continually, but without necessarily having complete voluntary control of our actions based on what we are seeing and hearing. In other words, conscious awareness of what we are seeing, or hearing, involves parts of the brain other than those involved with unconscious awareness.

How can we then represent an action? How do we define the notion of an "atomic" action? As discussed above, eating a taco is actually a complex sequence of actions, where we showed how, at one level, it can be broken down into a sequence. However, just how many component actions can a given action be broken down into? Ultimately, this is a physiological question, that probably goes down even to the cellular level, where we could, at least in principle, break down the flows of chemical and electrical signals that are relevant to the decision and action process.

b) Specifying the Who and What: States of the subject and object

Of course, independently of how atomic the decision is, it will involve a potential change of state of the subject and/or object. Thus, to characterise an interaction or a decision, we must be able to state in precise terms who/what is the subject/object and what is the action. In that sense, we need a space of possibilities and a set of variables that can describe the state of the subject/object and what actions are possible.

For the subject, we will take a set of state variables, $\{s_i(t)\}$, and for the object a set of state variables, $\{o_j(t)\}$. There are a couple of tricky points here with respect to how we define the state of subject and object – what labels do we attach? The "eating the taco" example can help to fix intuition:

- **Chris will eat/eats/ate the taco de carnitas**
- **The student will eat/eats/ate the taco de carnitas**
- **The Facultad de Medicina student will eat/eats/ate the taco de carnitas**
- **The Universidad Iberoamericana student will eat/eats/ate the taco de carnitas**

How we may describe the state of the subject depends on the information we have at hand. In principle, all four subjects are unique, as are the four objects. No two persons eating a taco are the same and no two tacos are the same – ever!

i) Intrinsic versus Extrinsic state variables

In describing the state of the subject, Chris, there will be **internal/intrinsic** state variables, $\{s_{Ii}(t)\}$, such as his age, his nationality, his BMI, was he hungry, is he a vegetarian, does he like carnitas, does he prefer carnitas to other available foods etc. There will also be **external/extrinsic**, $\{s_{Ei}(t)\}$, state variables that refer to the environment in which the action takes place – time of day, restaurant, family home, beach etc. Similarly, in describing the state of the object, taco de carnitas, there will be **internal/intrinsic**, $\{o_{Ii}(t)\}$, state variables, such as portion size, is it maciza, is it fresh etc. and, once again, **external/extrinsic** state variables, $\{o_{Ei}(t)\}$. In principle, the external variables for object and subject are the same, $\{s_{Ei}(t)\} = \{o_{Ei}(t)\}$, if we imagine we are partitioning the world into three non-overlapping elements – subject, object and environment (that which isn't considered as subject or object). We will call these variables, environmental variables, $\{E_i(t)\}$. We will take the number of subject, object and environmental state variables to be N_S, N_O and N_E respectively. Note that the extrinsic variables are very much aligned with the notion of a "niche", as in an ecological niche. In this case it may be that an interaction is more or less favoured in the presence of a certain configuration of the extrinsic variables. For instance, one is more likely to eat a taco if it is served fresh in view, as opposed to finding it on the floor. It is the extrinsic variable part that plays an important role in representing, for example, an "obesogenic" environment. A principle feature of the extrinsic variables is that they represent the "where" and "when" contexts of where a decision is made, and an action taken.

Note that the extraction of a set of objective environmental variables is not completely clear cut. As an example of when the environment state can be considered in the two different ways, consider the case of an interaction between a blind person and a deaf person, although we try to establish an objective set of environment descriptors, how it is perceived by subject and object is different to this objective set. Thus, if a blind person, as subject, is buying apples from someone else, the colour of the apples is not an environmental variable that can affect the state of the subject.

ii) Objective versus subjective state variables

When considering subject, object and environment variables it is important to distinguish between the objective values of those variables and the subjective values they are perceived to take by the subject or, potentially, the object. To explain: a taco de carnitas, as an object, has features that are objective and which can be measured accordingly, such as its size, its weight, its texture etc. However, it also has features that are subjective, such as it "looks delicious" or it "smells heavenly" or it "tastes good". These features can also include attitudes – "its disgusting" – for example, such as might be thought by a vegan. Thus, we must differentiate between objective variables associated with either the subject or the object or the environment, and subjective variables. The opinions of a meat-eating Mexican, a Mexican vegan and a Moslem will all be very different with respect to a taco de carnitas, although it is the same object for all.

Also of relevance are differences in the objective and subjective intrinsic variables of the subject. For instance, obese subjects when confronted by a taco de carnitas may perceive themselves to be overweight and not obese, and this may play a role in altering the probability of eating it. Similarly, the probability of eating it for two subjects, each of which suffers from hypercholesterolemia or hyperuricemia, may be quite different if one understands fully their dietary origins and their health consequences while the other does not.

iii) Specifying states and labels

In representing the subject, object and environment we are confronted with the question of what variables will be considered relevant. Additionally - what variables are measurable?

There are, of course, generic variables, such as age or gender, which are relevant to our decision-making processes. Nationality and ethnicity are two other generic ones. Socio-economic status and educational level? Of course. Our weight/height/BMI? Our religious beliefs? Our health status? Our family history? Our personal history? Our genes? And these are just some of the variables that we would consider to be relatively static. There is, in principle, no limit to the number of variables that might be deemed relevant to our decision making. And what about an object, such as a humble taco? Its price, its size, its freshness? And the environment? Restaurant, street locale, at home, at a fiesta, at work, morning/afternoon/night? What about: am I hungry? Just how much do I like tacos? How far do I have to walk to buy one? How much money do I have? And, further – do I know much about the health effects of tacos? Do I know that meat production is very bad for the environment?

We can think of the state variables as a set of labels that help us to understand interactions between subjects and objects, which in turn help us to understand the decision-making process and the subsequent actions taken. Thus, the label "hungry-not hungry" can help us to understand why a person ate something at a given moment in time. The label "vegetarian" can help us to understand why only a certain food type is eaten, while the composite label "hungry vegetarian" can help us to understand why a certain food type was eaten at a given moment in time. The meaning of these labels is enormously important. We also need to understand that a label is a summary that really represents a **class** of subjects or objects. Each subject or object is associated with a large number of labels, and each label in its turn represents a class of subjects or objects. In principle, with a sufficient number of labels, a subject/object can be defined uniquely as a set intersection of such labels, while a particular label will define a set union of those subjects/objects that possess that label or combination of labels.

There are several important features to understand about these labels. First of all, there is the question of to what degree they are objectively definable. For example, to understand the label "vegetarian" – as someone who eats only vegetables versus someone who doesn't eat meat – we also need to understand what a vegetable is and what meat is. In other words, to define the class we need to be able to define other classes that are implicit in the definition of the class of interest. Even more fluid, however, are labels where an objective definition is much more complex. For instance, with the label "hungry", do we take that label as a self-reported label? or as a label associated with a certain level of the hormone ghrelin? or a certain neuronal state etc.? What about happy, depressed, disappointed, tired, lazy etc.?

Related to these questions, another important aspect of the state variables/labels is their degree of permanence. For instance, "male/female" as a state variable is, to a large extent a permanent label and that label can help us understand a wide set of interactions. On the other hand, labels such as "hungry/not hungry", besides being subjective, are also quite transient. Moreover, within the state variables we must also account for what is in the mental model of the subject, and potentially the object, if the object is capable of having one. For example, memories of past events that are similar to the current situation can strongly affect our decision in the current situation.

We will consider the intrinsic subject state to be a N_S-dimensional vector, or we can also think of it as symbol string with N_S elements (labels):

$S(t) = (s_{I1}(t), s_{I2}(t),\ldots, s_{INS}(t))$

And the intrinsic object state to be a N_O-dimensional vector or analogous symbol string:

$O(t) = (o_{I1}(t), o_{I2}(t),\ldots, o_{INO}(t))$

and the environment to be a N_E-dimensional vector or analogous symbol string:

$E(t) = (e_1(t), e_2(t),\ldots, e_{NE}(t))$

These states will be composed of some variables that are objectively measurable, some that are subjective, some that are relatively permanent, some that are quite transient etc.

In specifying the subject, object and environment, in the context of natural language we usually mean a specific, unique subject and a specific, unique object. What differs is what information is at hand to make the specification unique. In specifying: "Chris ate the taco de carnitas?" we must ask: Is this a generic Chris or a specific Chris? In language it is, more often than not, implicit that "Chris" is a unique subject and not a generic representative of the class of "Chris". Similarly, with "the student ate the taco de carnitas" – implicitly there is the idea that although no further details about this student are to be had, it was a specific student, as is implicit in the use of the definite article "the", as opposed to "a student ate the taco de carnitas". Mathematically, we may account for this by asking to which **class** of subjects (C_S)/objects (C_O)/environments/(C_E) does a specific subject/object/environment belong? The class of "me" is the singleton, as there is only one "me". To understand the class of Chris' – as in "a Chris ate the taco de carnitas" – requires further assumptions as to class membership. Similarly, with "the student ate the taco de carnitas" versus "a student ate the taco de carnitas", in the latter case we must also make some assumptions about class membership. Thus, we must distinguish between information that is in principle obtainable – to differentiate "the student" from among many – versus that which is implicitly unobtainable, as in "**a** student". Note that the amount of information we have about the subject or object can be a function of time and also of the population considered – students versus students of the UNAM etc.

A final difficulty to point out is that we have no idea what constitutes a sufficiently complete set of state variables with which to describe a subject or object. In terms of decision making, the set of relevant labels for one decision and action can be quite different to those of another. We could posit the existence of a set of labels that cover all possible decisions or actions as opposed to the complete set that are relevant for a given decision/action. However, as there is no *a priori* way to specify a state adequately we can take a pragmatic approach: i) specify an initial set of measurable state variables; ii) determine the degree of predictability of those variables with respect to predicting a given decision/action; iii) add or subtract a variable to this set; iv) determine the degree of predictability of the new variable set with respect to predicting the given decision/action. If the predictability is enhanced on adding the variable, then we conclude that it is a relevant state variable for that decision/action, while if the predictability is not changed then we deem it to be irrelevant. Similarly, if the removed variable does/does not change the degree of predictability then we consider it to be relevant/irrelevant.

iv) **Counting states**

An important concept will be that of counting states. To count states, we need a statistical ensemble, as discussed above in the context of behaviour. In the case of human decision making there are several ensembles of interest. For instance, an ensemble of people at a moment in time or an ensemble of people, or a person, over time. Once we specify a state with a certain set of variables, and a measuring apparatus for each state variable, then we may determine how often that state occurs within our ensemble. For instance, if our ensemble is students of the UNAM, we may ask at a given moment how many report - feeling very hungry, quite hungry, neither hungry nor satiated, quite satiated, very satiated. We can then count how many students, n_{sh}, were in a hunger state, h. If there are N students, then $(N – n_{sh})$ were not in that hunger state. Similarly, we can take one student over a period of time and see when they reported the same, counting how many times they reported a hunger state over a given time interval. In both cases, however, we must realise that we arrive at counts on states that are > 1 only because a subject or object state is being approximated. We can call this approximation – **coarse graining** – and it corresponds to ignoring or being unaware of information that could distinguish between two states.

v) Interactions

We have previously defined an interaction as a unique event I(S,O,A). Now we can specify the subject and object states via $S = S(\{s_{Ii}(t)\}, \{e_i(t)\})$ and $O = O(\{o_{Ii}(t)\}, \{e_i(t)\})$. From this perspective an interaction is intimately linked to a specific subset of labels that defines the subject, object or environmental states. Thus, the labels "food consumer" and "food consumed" indicate the nature of the interaction, though the most appropriate labels might be "hungry student" and "taco de carnitas".

For the probability P(I(S,O,A)) that an interaction occurs, if S, O and E are the characteristics of that unique event, i.e., the definite article sense of S, O and E, then, clearly, P cannot be interpreted in a frequentist sense but must be interpreted in a Bayesian sense, i.e., it represents a plausibility or belief. However, if we consider the indefinite article sense of S, O and E then we may state: "a student ate a taco". Here, we may consider a population of students and a population of tacos, but the reference is with respect to a single event between a member of the subject class of students and a member of the object class of tacos. As with the concept of coarse graining states we can also coarse grain interactions and count them over an ensemble. For example, considering "some students ate some tacos" – if we coarse grain the subject state – ignoring differentiators between the students – and coarse grain the object state – ignoring differentiators between the tacos – then we may count how many "student eating a taco" interactions there were.

vi) Real versus virtual interactions

An important element here is whether the interaction is **real** or **virtual**. Real here means that there is a physical action and a physical object in a real, physical environment, all of which are observable. These interactions form part of an external ensemble, as discussed in Section 2d, while virtual refers to the fact that the interaction occurs as a mental construct, these interactions forming part of an internal ensemble. Thus, for example, we may imagine another person, as subject, eating a taco, as object, in a particular environment. In this case, we can still potentially assign subject, object and environmental states.

$S(t) = (s_{I1}(t), s_{I2}(t),\ldots, s_{INS}(t))$

$O(t) = (o_{I1}(t), o_{I2}(t),\ldots, o_{INO}(t))$

$E(t) = (e_1(t), e_2(t),\ldots, e_{NE}(t))$

As mentioned, the relevant features of a **real** subject, **real** object and **real** environment may be divided up into objective and subjective features. In other words, how a subject is perceived, or perceives themselves, or an object or environment can be quite different to reality. In the case of attitudes, it is not necessarily the case that a distinction can be made between reality and perception of reality. For a vegan, a taco de carnitas may appear "disgusting" even though it has been considered "appetizing" by thousands of non-vegans. However, people may also consider themselves to be normal weight when they are very overweight when referred to an objective scale, such as BMI. In the case of virtual interactions though, there is no objective anchor that can be held up as a baseline. In a virtual interaction the labels that we apply to a subject, which may be ourselves, an object and the environment, are what our mental model deems them to be.

c) Just how likely is a state, decision or action?

Up to now we have been setting the stage – defining interactions, decisions and actions, trying to show how to formalize these notions using the concept of specifying a subject, object and environmental state and a corresponding interaction and decision associated with a change of state. However, if we go to the level of every state and every action as being unique, then how may we do science? For instance, how can we understand why a certain decision is made or a certain action taken if every single one is unique? How can we ask how likely is it that a certain decision is taken, or action performed? How do we characterize behaviour?

We have emphasized that we can consider objective or subjective external ensembles as well as internal ensembles. In certain circumstances, as discussed, for an external ensemble we may consider a frequentist approach to probability. Generally, however, a Bayesian perspective is necessary. As an example, going back to statements such as: "Chris ate the taco de carnitas" or "the student ate the taco de carnitas", in this setting, there is no concept of how likely it is for Chris versus the student to eat the taco – if we consider "likely" to come from a frequentist interpretation of "likely = probable", where we would need a statistical ensemble (a population of events) to say how probable.

However, we may imagine constructing an external ensemble of interactions by collecting appropriate data. For example, watching Chris in his eating habits over time, or considering a group of students. What we must realize however, is that Chris at one moment in time is not the same as at another moment. Neither is one student the same as another. This means that, when we construct an ensemble, we are going to make an approximation as to the state of both the subject and object. However, this ensemble may be a real ensemble or a virtual one. For instance, if we consider the prior probability to eat the taco de carnitas, P(*eat the taco de carnitas*), how would this probability be computed. The unbiased decision would be to assign P(*eat the taco de carnitas*) = 0.5. However, if we asked a family member what they would estimate the probability of P(*Chris eats the taco de carnitas*) they would not flip a coin. They would likely say "high", if they know that Chris likes carnitas, and "low" if he doesn't. How do they do this? They have a virtual ensemble of Chris/taco events in their mental models, which allows them to assign a probability to the event. Whether this probability extracted from a virtual world is an accurate representation of what Chris will do next in the real world is, of course, a matter of experiment.

Thus, we can have two models for Chris and tacos – one that is the belief of the family member and one that is associated with a set of empirical observations of under what circumstances, subject, object and environmental variables, Chris eats the taco. Again, if we make a detailed specification of these states then it is impossible to create an ensemble of such events. To create an ensemble, we either have to coarse grain the subject/object/environmental variables or to consider a wider group that shares labels with Chris and try to **infer** what Chris would do from an extrapolation of different facets of the group behaviour. In other words, we could consider a population of people, some of whom share the label "man" with Chris, some of whom share the label "English", some who share the label "age 55-65", some who share the label…, etc. This inference can be done using multiple statistical or machine learning models. It does require however, that we have a real ensemble of persons. We can also, of course, compute probabilities in frequentist terms directly if we stick to just a small number of labels in the population. Thus, to determine how many students ate taco de carnitas today among a population of students is possible.

We can also relate subjective and objective probabilities by asking, for example, how likely are you to take action A and then use empirical data to determine the corresponding objective probability, at either the individual level, if we have such data, or at the group level by determining the characteristics of those in the group that did/didn't take action A given that they said they would/wouldn't.

i) Predictability

Thus, taking a decision to be a choice between alternative actions, including no action, we can consider

$$P(I(\mathbf{S}(\{s_{Ii}(t)\}, \{e_i(t)\}), \mathbf{O}(\{o_{Ii}(t)\}, \{e_i(t)\}), A_k)) \qquad (1)$$

which represents the probability for a subject S in the state $\mathbf{S}(t) = \{s_{Ii}(t)\}$ to take the action A_k given an object in a state $\mathbf{O}(t) = \{o_{Ii}(t)\}$ and an environment in a state $\mathbf{E}(t) = \{e_i(t)\}$. Here, we are still allowing for the fact that the environment state may be different for the subject and object. In the case where the environmental variables are common, or we wish to represent the environment objectively, independently of the subject and object states, then we may separate them out and write

$$P(I(\mathbf{S}(\{s_{Ii}(t)\}), \mathbf{O}(\{o_{Ii}(t)\}), \mathbf{E}\{e_i(t)\}), A_k)) \qquad (2)$$

As an example of when the environment state can be considered in the two different ways, consider the case of an interaction between a blind person and a deaf person, although we try to establish an objective set of environment descriptors, how it is perceived by subject and object is different to this objective set.

If we take the example of A_k as an action (k = 1)/no action (k = 0) choice, then

$P(I(\mathbf{S}(\{s_{Ii}(t)\}, \{e_i(t)\}), \mathbf{O}(\{o_{Ii}(t)\}, \{e_i(t)\}), A_1)) = 1 - P(I(\mathbf{S}(\{s_{Ii}(t)\}, \{e_i(t)\}), \mathbf{O}(\{o_{Ii}(t)\}, \{e_i(t)\}), A_0))$

$P(I(\mathbf{S}(\{s_{Ii}(t)\}, \{e_i(t)\}), \mathbf{O}(\{o_{Ii}(t)\}, \{e_i(t)\}), A_1))$ is a function on an $N_A = N_S + N_O + N_E$ dimensional space. Equation (1) can also be viewed as a prediction model, in that if S, O and E are such that $P(S, O, E, A_k) \sim 1$ then we may say that, if we see the subject, object and environment in these states, it is very likely that a decision is made to carry out the action A_k. In other words, these state variable configurations are predictive of the action. Similarly, if $P(S, O, E, A_k) \sim 0$ it is very unlikely that the action A_k is carried out and the corresponding state variable configurations predict that the action will not be carried out. If $P(S, O, E, A_k) \sim P(A_k)$ then the corresponding state variable configurations are not predictive.

We can generalize Equation (1) to the space of all actions as

$$P(I(\mathbf{S}(\{s_{Ii}(t)\}, \{e_i(t)\}), \mathbf{O}(\{o_{Ii}(t)\}, \{e_i(t)\}), \mathbf{A})) \qquad (3)$$

where $\mathbf{A} = (A_1, A_2,\ldots,A_k,\ldots, A_{NA})$ is a vector representing the N_A considered actions, including the base possibility of "no action". Considering (1) and (2) as joint probability distributions, then Equation (3) represents a set of N_A numbers such that

$$\sum_{k=1}^{N_A} P(I(\mathbf{S}(\{s_{Ii}(t)\},\{e_i(t)\}), \mathbf{O}(\{o_{Ii}(t)\},\{e_i(t)\}), A_k)) = 1 \qquad (4)$$

i.e., the subject and object have to do "something", even if that something is nothing. This is to account for the fact that the decision process must lead to a result. As we have emphasized, how to interpret Equations (1), (2) and (3) depends on how we interpret the concept of probability and the associated notion of statistical ensemble. However, whether we interpret it in a strict Bayesian belief sense or not, as emphasized, there always has to be some notion of an ensemble, be it an objective one or a virtual one. In this case, the subject, object and environmental variables, $\boldsymbol{S}$, $\boldsymbol{O}$, and $\boldsymbol{E}$ are all associated with perceptions rather than objective reality. Now, Equation (3) becomes

$$P(I(\boldsymbol{S}(\{s_{Ii}(t)\}, \{e_i(t)\}), \boldsymbol{O}(\{o_{Ii}(t)\}, \{e_i(t)\}), \boldsymbol{A})) \qquad (5)$$

Although it is not at all clear that in the virtual world Equation (4) holds. From Equation (1) we can also consider the conditional probability

$$P(A_k \mid I(\mathbf{S}(\{s_{Ii}(t)\}, \{e_i(t)\}), \mathbf{O}(\{o_{Ii}(t)\}, \{e_i(t)\}))) \qquad (6)$$

which represents the probability that the action A_k is taken conditioned on the subject, object and environment states as implicit in the interaction I.

5) The Decision Landscape

Equation (6) can naturally be interpreted in a geometrical sense, where it defines for us a **Decision Landscape**, which tells us under any circumstance how likely it is that the action is taken or not, or which action in the case of alternatives, as a function of the state variables. In this case, $P(A_k \mid I(\mathbf{S}(\{s_{Ii}(t)\}, \{e_i(t)\}), \mathbf{O}(\{o_{Ii}(t)\}, \{e_i(t)\})))$ represents a height function on a $N_A = N_S + N_O + N_E$ dimensional base space of the subject, object and environment variables. If these variables are in such a state that $P(\mathbf{S}, \mathbf{O}, A_1) > 0.5$, then it is more likely that the action is taken rather than not. For states where $P(\mathbf{S}, \mathbf{O}, A_1) \sim 1$, then it is very likely that the action is taken, while if $P(\mathbf{S}, \mathbf{O}, A_1) \sim 0$ it is very unlikely that the action is taken.

Equation (6) also represents the output of a prediction model, such that it predicts how likely is the action, given the state of the subject, object and environment. Note that we are here thinking of an individual decision/action. However, as stated above, this requires a notion of potentially unraveling the full causal sequence of atomic decisions and actions that compose what we typically think of as an action – such as eating. For instance, the decision of "don't eat the taco" can enter at any point in the process from the first physical approach to the taco up to the point at which the first bite is swallowed. Alternatively, only part of the taco may be eaten.

However, putting these complications aside, how might we consider Equation (6) in the empirical domain? i.e., how can we measure it? Let's go back to the examples of: "Chris ate the taco de carnitas". If the subject and/or object and/or environment are unique, then really, we can go no further with Equation (6), other than in a Bayesian sense of assigning a subjective belief. The problem with this, as in the example of a friend saying that you are likely to eat the taco de carnitas, is that, even though the friend knows you well and from their virtual ensemble can estimate that its highly likely that you will eat the taco, they cannot say why in any really useful sense. This is because all they can give us is the output of equation (6) taking into account only the base information "Chris" and "taco de carnitas". They would not be able to disaggregate the probability to be able to determine what particular factors played an important role and which not. Indeed, this is even the case when trying to understand Equation (6) as the subject. We are not aware of the relative weights of the factors that enter into our decision other than we make an attempt to self-report them.

Using either an external or an internal ensemble for Equation (6) we can consider it from a "landscape" point of view, similar to the concept of a fitness landscape in evolutionary biology [22]. However, given that the relation between the action and the state variables is not static, a more appropriate analogy is that of an "effective fitness" landscape [23, 24] wherein the height of a particular point in the base space can change over time. This, indeed, is a way to visualize behaviour change, where a particular point in the space can change its height so that before the behaviour change, for a particular adverse action A_k, $P(A_k) > 0.5$, while after the behaviour change it is $P(A_k) < 0.5$, signifying that the behaviour change has reduced the probability of the adverse decision and action.

In Figure 1 we illustrate a simple decision/action landscape for a decision/action associated with the consumption of junk food as a function of two subject state variables – educational level, X_1, and degree of cognitive stress, X_2. The base plane is associated with $P(A_k)$, i.e., the probability to consume junk food independently of a specific configuration of the state variables. The decision/action threshold is such that for those values of the state variables where $P(\text{consume junk food} \mid X_1\, X_2) > 0.5$ there is more likelihood that the subject consumes the junk food in that state than otherwise.

A real Decision landscape involves hundreds if not thousands of state variables in which case the visualization is more problematic. As with fitness landscapes however, we believe that a lower dimensional visualization is useful. The interpretation of this landscape in terms of reduction of junk food consumption is to increase educational levels while maintaining moderate levels of cognitive stress.

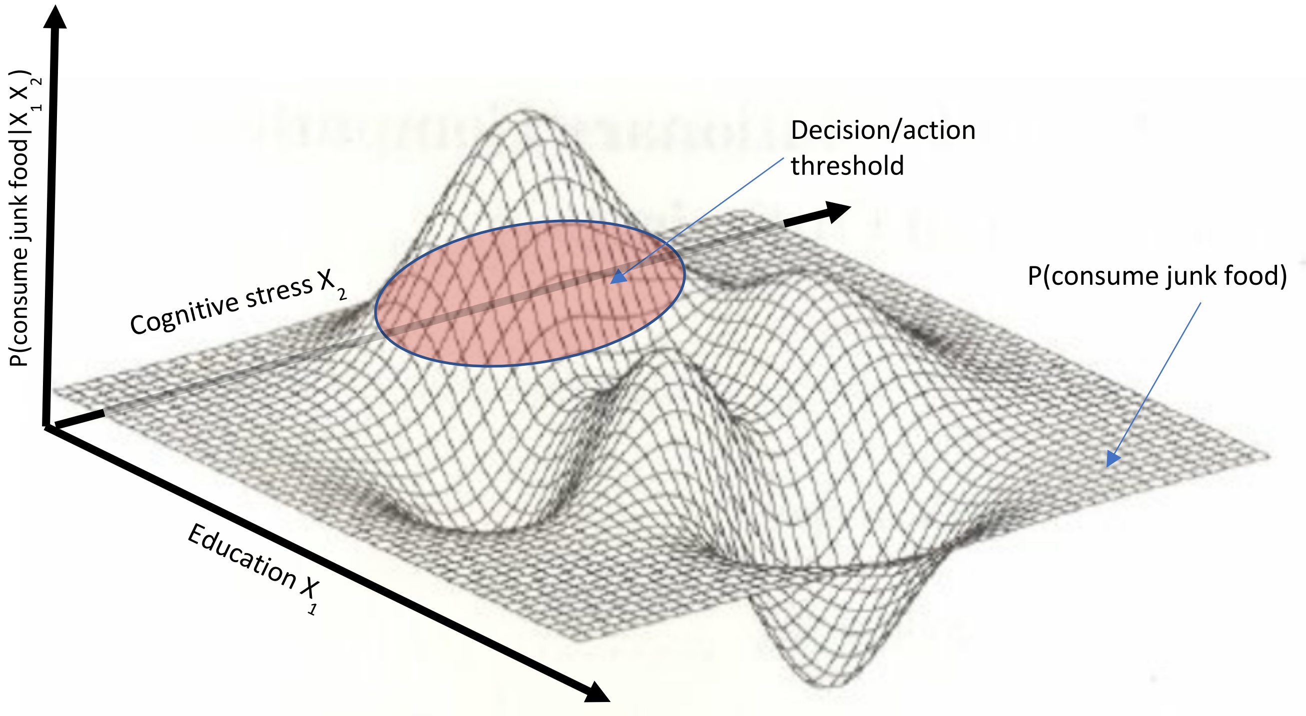

Figure 1: Simple illustration of a Decision/action landscape.

The meaning and interpretation of the landscape also depends on the particular ensemble used to calculate it. For instance, we could have used an external ensemble of persons of differing educational levels where their level of cognitive stress was evaluated. The consumption of junk food could have been objectively observed or self-reported. Similarly, the degree of cognitive stress may have been measured objectively or may also be self-reported. In principle, we could also have considered an ensemble over time for a given person. The probabilities could also have been estimated as Bayesian beliefs, either by an external observer or by a particular subject. We could also compare and contrast the decision landscapes associated with different ensembles. An interesting example there is that the height function is objective, measured using a suitable external ensemble, whereas one or more of the state variables is an internal variable of the subjects considered. For example, it has been found that the self-perception of Body Mass Index (BMI) can be distorted relative to true BMI and this can lead to behaviours, such as "not dieting", that would have had a higher probability to be implemented if the self-perception of BMI was aligned with real BMI [25].

a. When is a decision a bad one versus a good one?

Up to now we have made no reference to the concept of whether or not a decision was "good" or "bad", which, in its turn, is intimately related to the question of why we make a certain decision or perform a certain action. The evaluation of good or bad is related to the outcome of the decision/action with respect to one or more metrics of good/bad. The traditional view of rational decision making is that the decision is made so as to choose the alternative that maximizes the expected utility [26]. Besides the normal critiques around bounded rationality etc. we can also wonder to what extent this captures the right idea in the first place. Most work on expected utility has been associated with "gambling" situations where there is one clear payoff function – money earned. Extensions can include risk but within the context of a unique utility function that has one input. However, in the vast majority of situations there are multiple "utility" functions that are relevant.

Let's take a simple example that is relevant for weight gain: deciding to take the stairs versus the elevator to get to your office. What are some "utilities" that could enter there? DT = the time difference between taking the stairs and taking the elevator; DE = the difference in physical energy expended in one route versus another; DH = the relative perceived health benefit of one versus the other (think how this can change pre-COVID versus post-COVID!); DS = the socialization benefit in the case you would take one versus the other with coworkers. There are others. Of course, one could invent a single unique utility function that balanced tradeoffs between these outcomes. However, the relative value of one versus the other is also a function of subject, object and environment states. For example, if one is in a tired or lazy state (subject effect) then the elevator will be more likely than if not. If the elevator is particularly small, or if the staircase is particularly steep (object effect), this may affect the decision. If there is information posted next to both (environmental effect) delineating the health benefits of one versus another then that also may affect the decision.

To formalize this: we consider N_v value functions: $\mathbf{V} = (v_1, v_2, \ldots, v_{N_v})$, and a corresponding change, $D\mathbf{V}$, in these value functions given a certain action A_k – $D\mathbf{V}(A_k) = (Dv_1(A_k), Dv_2(A_k), \ldots, Dv_{N_v}(A_k))$. So, every action can lead to a change in these values functions. Note that $D\mathbf{V}(A_k)$ can take different values depending on where the measurement is made – pre-action versus post-action. Post-action, $D\mathbf{V}(A_k)$ represents the real or perceived payoffs of the action, i.e., they are outcomes. In general, these will be subjective evaluations, although in some cases the perceived change in value may be compared to a real one. For example, the perceived time taken via one alternative versus another can be compared with the real time taken. In the case of a pre-action evaluation $\langle Dv_1(A_k)\rangle$ represents the predicted value change due to the action. Here, $\langle\ldots\rangle$ does not necessarily mean that it is an expected value calculated as a weighted sum over a probability distribution of outcomes, although from an external ensemble perspective it could, in principle, be calculated as such; rather, it means that we have an internal prediction model for estimating what the change in value will be.

We then posit that the probability to take the action A_k is

$$P(A_k \mid \langle D\mathbf{V}(A_k)\rangle) = P(A_k \mid \langle Dv_1(A_k)\rangle, \langle Dv_2(A_k)\rangle, \ldots, \langle Dv_{N_v}(A_k)\rangle) \tag{7}$$

Thus, the probability to take the action A_k is conditioned on the predicted payoffs from the action along a set of distinct value functions.

We now have a formalization of our notion of a good versus bad decision: a decision is "good" versus "bad" with respect to a given value function v_i if $Dv_i(A_k) > 0$ ("good" decision) versus $Dv_i(A_k) < 0$ ("bad" decision). Of course, the question then is to what degree is our decision making "frustrated"? What I mean by this is that it is not possible to perform an action such that $Dv_i(A_k) > 0$ for all v_i. This would be the case, for example, in the stairs-elevator situation if the elevator was slow. In other words, DT(*stairs versus elevator*) > 0 but DE(*stairs versus elevator*) < 0. In this situation "you can't have your cake and eat it".

b) Predicting value

If we posit that a decision is made, and an action taken, according to the predicted changes in a set of value functions then we must then ask – how are those predictions made?

Here we will assume that there is a prediction model for each value function change. Thus

$$P(Dv_i(A_k) \mid \mathbf{S}(\{s_{Ii}(t)\}, \{e_i(t)\}), \mathbf{O}(\{o_{Ii}(t)\}, \{e_i(t)\}) \qquad (8)$$

In other words, we predict what the probability is for a change in the value function v_i given the subject, object and environment states. Thus, for example, in the stairs-elevator example – if the subject is in a "very tired" state, then the probability for a large perceived increase in effort, DE, to take the stairs would be higher than in the "non-tired" state with the consequence that in equation (6) the probability function will be such that P(*take the stairs* | $\langle$DE(*take the stairs*)$\rangle_1$) < P(*take the stairs* | $\langle$DE(*take the stairs*)$\rangle_0$), where $\langle$DE(*take the stairs*)$\rangle_1$ is the predicted effort for taking the stairs given that the subject is in the state 1 = "very tired" and $\langle$DE(*take the stairs*)$\rangle_0$ is the predicted effort for taking the stairs given that the subject is in the state 0 = "not tired". The predicted change in v_i we then take to be

$$\langle Dv_i(A_k)\rangle = F(P(Dv_i(A_k) \mid \mathbf{S}(\{s_{Ii}(t)\}, \{e_i(t)\}), \mathbf{O}(\{o_{Ii}(t)\}, \{e_i(t)\})) \qquad (9)$$

for a given function F( ) that maps the probability function for the value function changes conditioned on the subject, object and environment states into an "expected" change where, again, we emphasize that this does not mean that $\langle Dv_i(A_k)\rangle$ is calculated as a weighted sum of probabilities.

We may ask what the difference is between Equations (6) and (7), given that they both represent the probability for a given action. The difference is that in Equation (7) we are trying to account for the "why" a particular decision is made. Equation (6) is taking a more empirical approach in that, at least in principle, it is trying to relate some observable state variables to actions taken, whereas Equation (7) accounts for the fact that the reason a decision is made is due to the impact that it has on the predicted changes in the value functions that are relevant to the decision maker. Equation (8) then relates the predicted change in a given value function to the subject, object and environment states. In this way (7) and (8) together are equivalent to (6). The difficulty with Equations (7) and (8) is that the value functions as intermediaries in our mental models are not directly observable.

6) The Conductome

Our Decision Landscape effectively represents what we might terms a "decision-ome", as knowing the probability given in Equation (6) as a function of the different subject, object and environment states allows us to map out the likelihood of a decision and action for any state configuration. In this sense, the subject, object and environment variables/labels, in analogy with the genome and other omes, represent the universe of variables that are relevant for understanding that decision/action.

If we consider the notion of **conduct** to mean that under the same or similar conditions the same decision/action is taken, then the **Conductome** is the same thing as the decision-ome. The concept of **conduct** as mentioned at the beginning enters when a set of correlated decisions are considered and we seek to understand the "why" behind the observed or inferred behaviour.

a) An example

In order to show that the above discussion is not purely hypothetical, we will here construct a specific example of a Conductome. The data we will use is that of Project 42, an interdisciplinary project researching the origins and risk factors for obesity and metabolic disease that is constructing a "deep" dataset that contains thousands of variables – genetic, physiological, sociological, psychological, anthropometric, epidemiological and behavioral – associated with more than 3000 university workers, students and academics at the Universidad Nacional Autónoma de México. The specific example of a behaviour that we will consider is that of sedentariness, as proxied by the answer to the question:

"Do you exercise midweek?"

A motivation for this question is obviously to link the answer as a potential risk factor to the prevalence of obesity and metabolic disease. However, the main drawback of this is that, to a large degree, we already know the answer: obesity is strongly correlated with overconsumption of food and sedentariness. In other words, obesity as a health status is known to be related to sedentariness as a behaviour. The important question then is not so much the link between obesity and sedentariness but, rather, the various factors that lead to sedentariness as a risky behaviour and, furthermore, the question of whether or not that behaviour can be changed and, if so, how?

In the language of the Conductome, we take C as the class represented by those who answered No to the question "Do you exercise midweek?" Of course, we do not take this to be a complete representation of the concept of sedentariness, which can be associated with many different facets. We wish to construct the Conductome, $P(C|\mathbf{X})$, for this conduct. We will restrict attention here to a set of variables as predictors associated with a questionnaire applied to 292 participants in 2019. The total number of data elements, i.e., the sum of the potential question responses over all questions asked, was 1713. Thus, in effect, $\mathbf{X}$ is a 1713-dimensional vector, where each dimension has a binary yes/no response. As an example, one question is: "What housework/chores do you do?" with responses: childcare, cleaning the bathroom, dusting, sweeping, cleaning the floor, making the bed, cooking, washing dishes, washing clothes or going to the supermarket. Each potential response is associated with a yes/no, which then represents 10 of the 1713 total responses.

We consider first the univariate relations $P(C \mid X_i)$ for a particular Conductome variable X_i. In order to test for statistical significance, we use the binomial test $\varepsilon(C|X_i)$ of section 3b to determine if the presence of the conditioning factor is inconsistent with the null hypothesis that the probability for the conduct C is $P(C)$. The full Conductome probability distribution $P(C \mid \mathbf{X})$ can be constructed using different techniques. A very useful one is to use Bayes theorem and then the Naïve Bayes approximation [27]. Explicitly,

$$P(C \mid \mathbf{X}) = P(\mathbf{X} \mid C)P(C)/P(\mathbf{X})$$

with the likelihood function $P(\mathbf{X} \mid C)$ approximated as

$$P(\boldsymbol{X}|C) = \prod_{i=1}^{N} P(X_i|C)$$

A simplification can be made can be obtained by considering

$$S(C|\boldsymbol{X}) = \ln\left(\frac{P(C|\boldsymbol{X})}{P(\bar{C}|\boldsymbol{X})}\right) = \sum_{i=1}^{N} s_i + \ln\left(P(C)/P(\bar{C}\right)$$

where $s_i = \ln(\frac{P(X_i|C)}{P(X_i|\bar{C})})$ with $\bar{C}$ being the complement of the set C, i.e., those participants who do exercise midweek. If the set of Conductome predictors $\mathbf{X}$ is such that $S(C|\boldsymbol{X}) > 0$ then those predictors indicate enhanced risk of sedentariness, in that the person is more likely than not to not exercise midweek. If $S(C|\boldsymbol{X}) < 0$, however, the contrary is the case. s_i is effectively the relative weight of the risk/protective factor i. In this case the Conductome is a sum of contributions from each variable.

In Table 1 below we see the most statistically significant predictors for the conduct under consideration. The table shows that of the 292 participants, 120 did no exercise midweek, corresponding to 41% of the participants. The first line represents the most statistically significant predictor – childcare during the week – where the number of participants who are involved in such childcare is 41, of whom 29 do not exercise midweek, corresponding to 70.7%. The statistical reliability factor 3.86 is the number of standard deviations of the binomial distribution that 70.7% is not consistent with the null hypothesis of 41%. The predictive model weight is just s_i in the above Naïve Bayes approximation. In the final column we have attempted to hypothesize what the causal relationship between C and X_i may be. Thus, it is intuitively reasonable to imagine that looking after children can have a significant impact on the possibility of doing exercise. A particular characteristic of these results is how different behaviours/conducts can be related, with particular types of housework/homecare being particularly significant, as well as eating habits, with eating in the street being highly linked to not doing exercise (88.9%). We can also see that extensive travel time (60min) in public transport is a significant factor. This factor, along with others, reflects environmental factors in which decision making must be carried out. All in all, these factors strongly reflect the difficulty of exercising when the time is filled with other activities – housework, transport etc.

In the same way we may determine what the principal factors are in being non-sedentary midweek. In Table 2 we show those most statistically significant factors that are negatively correlated with sedentariness. Of special interest here is the presence of educational level (doctoral level) as a significant predictor, as well as occupation (researcher), with only 8.3% of researchers not exercising midweek and 19.2% of doctoral level participants. Transport in the participant's own vehicle and shorter travel times (30min) are also seen as significant factors. Also significant is the reporting of free time by the participants.

Pregunta	Respuesta	Número de personas con X	Número de personas que no hacen ejercicio y X	N	Nc	% que no hacen ejercicio	% que no hacen ejercicio y X	Predictive model weight (score)	Statistical reliability (Epsilon)	Causa o consecuencia
¿Qué quehaceres realiza?: Cuidado de niños	Sí	41	29	292	120	41.10%	70.73%	0.38	3.86	Causa
¿Qué tan regular es su horario para ir a dormir?	1 - 2 hrs	17	14	292	120	41.10%	82.35%	0.67	3.46	Ambos
¿Realiza ejercicio en fin de semana?	No	182	97	292	120	41.10%	53.30%	0.06	3.35	Ambos
¿A qué hora se transporta a su casa?	15:00	32	22	292	120	41.10%	68.75%	0.34	3.18	Causa
¿Cuántas horas duerme entre semana?	4-5 horas	65	39	292	120	41.10%	60.00%	0.18	3.1	Consecuencia
¿Aproximadamente cuantas horas libres tiene al día entre semana?: No sé	Sí	24	17	292	120	41.10%	70.83%	0.39	2.96	Causa
¿Dónde come entre semana?: Posición 2	En puestos de la calle	9	8	292	120	41.10%	88.89%	0.9	2.91	Ambos
¿Qué quehaceres realiza?: Lavar el baño	Sí	172	89	292	120	41.10%	51.74%	0.03	2.84	Causa
¿Qué quehaceres realiza?: Sacudir	Sí	158	82	292	120	41.10%	51.90%	0.03	2.76	Causa
¿En qué tipo de vehículo se transporta de su casa al trabajo? y ¿Cuánto dura cada uno aproximadamente EN MINUTOS?: Metro: Valor	60 min	11	9	292	120	41.10%	81.82%	0.65	2.75	Causa
¿Cómo consigue sus colaciones?: La compro en un puesto	Sí	50	30	292	120	41.10%	60.00%	0.18	2.72	Ambos
¿Qué quehaceres realiza el fin de semana?: Cuidado de niños	Sí	60	35	292	120	41.10%	58.33%	0.15	2.71	Causa
¿Dónde desayuna? Seleccione por orden de frecuencia.: Posición 1	En la cocina del trabajo	27	18	292	120	41.10%	66.67%	0.3	2.7	Ambos

Table 1: Principle Conductome risk factors for Conduct = No exercise midweek

We can also put these Conductome results into the format of a Decision/Conduct Landscape as is seen in Figures 2 and 3 for two Conductome factors – what household work is done by the subjects and their occupation respectively. In Figure 2 we see that the principal household work that is a risk factor for the conduct = no exercise midweek is looking after children, while in Figure 3 we see very large differences for different occupations, with less than 10% of researchers not exercising midweek versus 75% for vigilantes.

Pregunta	Valor	Respuesta	Número de personas con X	Número de personas que no hacen ejercicio y X	% que no hacen ejercicio	% que no hacen ejercicio y X	Predictive model weight (score)	Statistical reliability (Epsilon)
¿En qué tipo de vehículo se transporta de su casa al trabajo? y ¿Cuánto dura cada uno aproximadamente EN MINUTOS?: Auto propio	Y	Sí	164	55	41.10%	33.54%	-0.3	-1.97
Cintura	(8.199, 76.28]		30	7	41.10%	23.33%	-0.52	-1.98
¿Aproximadamente cuantas horas libres tiene al día entre semana?: Tarde (En Horas)	Y	Sí	111	35	41.10%	31.53%	-0.34	-2.05
¿Aproximadamente cuantas horas libres tiene al día en fin de semana?: Noche (En Horas): Valor	2		40	10	41.10%	25.00%	-0.48	-2.07
¿Dónde realiza la mayoría de su ejercicio?	A2	Calle	18	3	41.10%	16.67%	-0.7	-2.11

¿Cómo considera que es su comida?	A4	Ligero	25	5	41.10%	20.00%	-0.6	-2.14
¿Cómo realiza su jornada laboral? y ¿Cuánto tiempo (en HORAS) aproximadamente? En movimiento: Valor	6		16	2	41.10%	12.50%	-0.85	-2.32
¿Aproximadamente cuantas horas libres tiene al día entre semana?: Mañana (En Horas): Valor	1		16	2	41.10%	12.50%	-0.85	-2.32
¿Aproximadamente cuantas horas libres tiene al día entre semana?: Tarde (En Horas): Valor	2		30	6	41.10%	20.00%	-0.6	-2.35
¿Aproximadamente cuantas horas libres tiene al día entre semana?: Mañana (En Horas)	Y	Sí	40	8	41.10%	20.00%	-0.6	-2.71
¿En qué tipo de vehículo se transporta de su casa al trabajo? y ¿Cuánto dura cada uno aproximadamente EN MINUTOS?: Auto propio: Valor	30		27	4	41.10%	14.81%	-0.76	-2.78
Grado de estudios	Doctorado		47	9	41.10%	19.15%	-0.63	-3.06
Puesto	Investigador		24	2	41.10%	8.33%	-1.04	-3.26
¿Realiza ejercicio en fin de semana?	Y	Sí	107	23	41.10%	21.50%	-0.56	-4.12

Table 2: Principle Conductome factors for Conduct = Exercise midweek

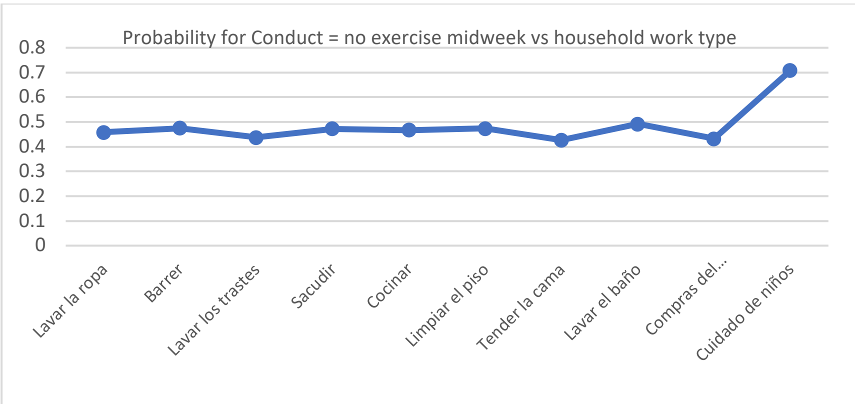

Figure 2: One-dimensional Decision/Conductome landscape for Conduct = No exercise midweek and risk factor = type of household work

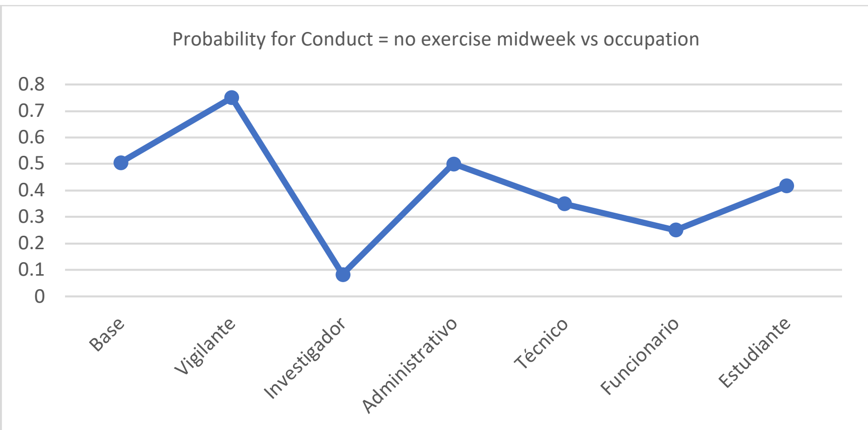

Figure 3: One-dimensional Decision/Conductome landscape for Conduct = No exercise midweek and risk factor = occupation

6. Conclusions

The solution of the world's principal problems, such as the obesity epidemic and its consequences, have shown an enormous resistance to improvement, in spite of a huge investment in both human and economic capital. Although we may legitimately recognise that these problems are very "complex", this has not led to any practical improvement in our ability to confront them. This complexity is chiefly associated with the fact that it is our conduct that is the root cause of these problems, and it is to a deeper understanding of behaviour that we must look to for solutions. In this chapter we have argued that the complexity of human behaviour requires an "omic" perspective, whereby the totality of factors that affect or influence a given behaviour, and which cross both scales and disciplines, must be considered in order to be able to both understand and predict human behaviour as well as identify potential interventions for changing it. We have outlined some of the conceptual and theoretical elements that we believe are crucial for the Conductome and, importantly, we have shown that the construction of a Conductome for a behaviour - sedentariness – that is highly relevant for the obesity epidemic, is feasible.

A key component of our approach, and a requirement for constructing the Conductome, is the obtention of data that transcends disciplines, and which can be used to link a range of relevant behaviours, as effects, to their causes, both intrinsic and extrinsic. A second component is the use of advanced modelling tools, such as machine learning, for the analysis of such multi-scale data and the construction of explicit prediction models for a given conduct. The further understanding, interpretation and utility of these data and models requires integrated, interdisciplinary teams and a close collaboration with both government authorities and the general public as out future depends on the decisions we make now and in the future.

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