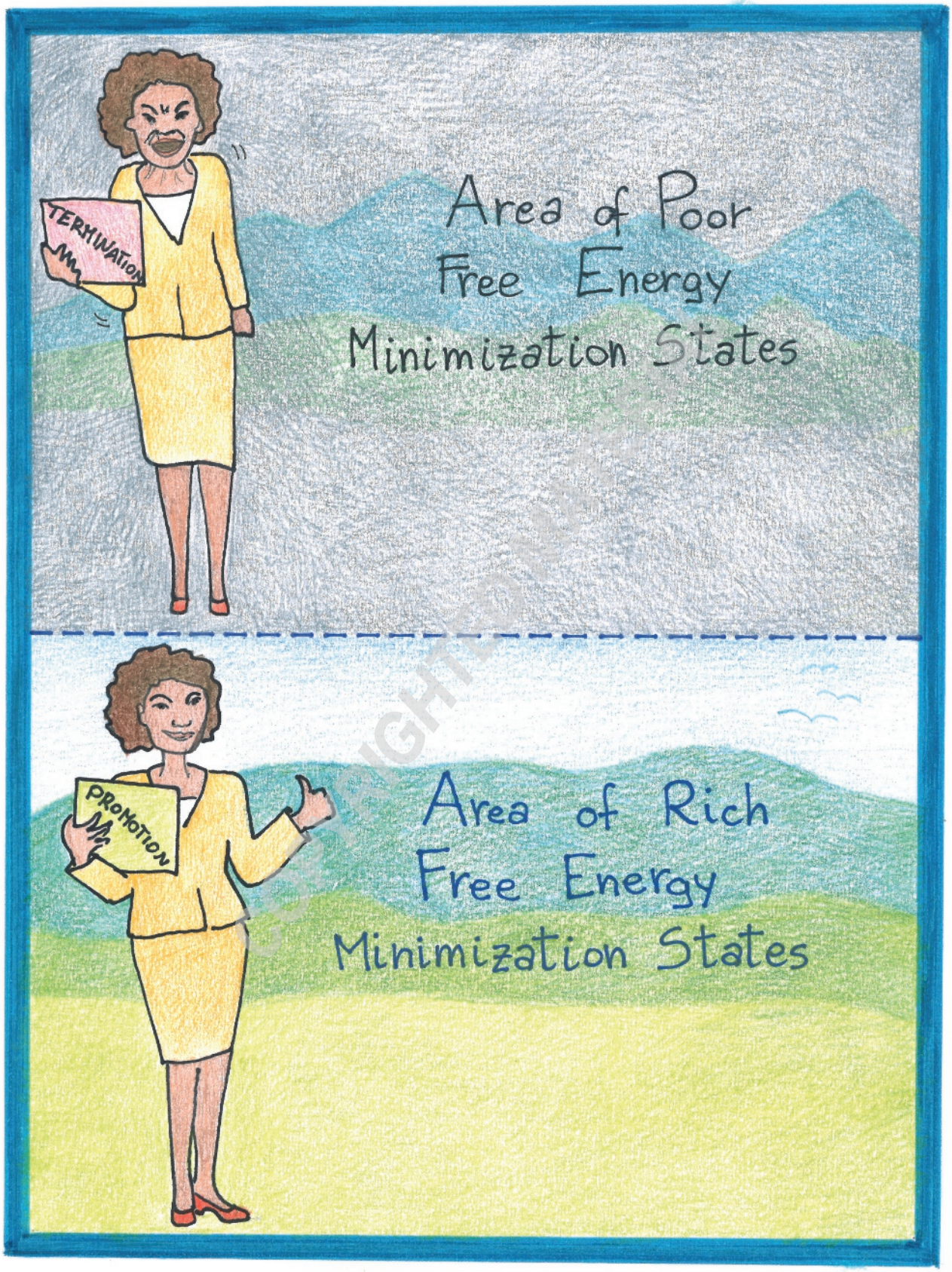
TERMINATION
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Chapter 1

THE UNDERLYING BIOMECHANICS OF OUR BRAIN

Mindfulness-based Strategic Awareness Training Comprehensive Workbook: New approach Based on Free Energy and Active inference for Skillful Decision-making, First Edition. Juan Humberto Young.
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1.1 Flourishing in a World of "VUCA": Is it Possible?

We live in a world where Volatility, Uncertainty, Complexity, and Ambiguity, the so-called VUCA environment, is becoming more acute, accelerated, and pervasive. For example, the fatal effects of COVID-19, a viral pandemic, began in Wuhan province in China. In less than two weeks, its impact was felt in most parts of the world, with millions of people infected around the globe and thousands of deaths resulting from the pandemic. Another example is the widely circulated video of a police officer in the USA with his knee on the neck of an Afro-American until he died of asphyxiation, triggering a chain reaction of events and protests in the USA and worldwide. More recently the deadly European fight between two ethnically very close groups of people affecting the whole world is another more contemporary example of VUCA in the world. The notion that we live in a globalized "VUCA" world is now an accepted view widely shared by the general public and academia alike, and amply reported and manifest in the media.

The recognition that our lives are embedded in a volatile, complex, uncertain, and ambiguous world suggests an essential question: can we flourish and live to our full potential under the reality of VUCA? If the answer is no, we have no choice but to give up and wait for the final dissipation of life. However, if the answer is yes, the essential issue should be: how can we achieve a flourishing life amid an increasingly disruptive world?

A critical premise of this workbook is that one can increase flourishing levels by making wise, strategic decisions, minimizing our quota of predictions errors, and taking skillful actions that don't harm ourselves, others, and the environment. This premise suggests that continuously training and developing the art and science of strategic and skilled decision-making pays a "high quality of life dividend" as we become more autonomous, competent, and able to cultivate harmonious relations in life.

Before contemplating how to train for skillful decision-making, I believe it is valuable and necessary to first look at what our brains do. This is because the brain is, so to speak, the Chief Executive Officer (CEO) of our emotional, cognitive, and physical make-up. Nothing happens in our lives without the presence of our brain CEO; it is where the processing of all our experiences happens. We gain information and build knowledge used to decide and mobilize action through the brain. Thus, understanding the mechanics of the brain is essential to identify the elements and levers that need to be intentionally trained to increase our chances of a flourishing life by achieving a low average of prediction errors and a high level of skillful decision-making in a world of VUCA.

1.2 Free Energy Minimization: The Motivation Behind What the Brain Does

For decades, the dominant framework about what the brain does has been that it is in the business of reacting to our sensory stimuli. According to this framework, the brain responds to our impulses to accommodate its emotional, cognitive, and motoric infrastructure and make sense of what is happening in the external and internal world or in both aspects of an individual's life. This sensorial reactive paradigm has been increasingly questioned in the last 20 years, as scientists discovered that this would

be an inefficient way of operating and too complex to maintain. "If your brain were merely reactive, it would be too inefficient to keep you alive. You are always being bombarded by sensory input… A reactive brain would bog down like your internet connection does when too many of your neighbors are streaming movies from Netflix… It would also be too expensive, metaphorically speaking, because it would require more interconnections than it could maintain." (Feldman Barrett, 2017, p. 60).

If the brain is not reacting to sensory inputs, what does it do then? The consensus in a growing group of neuroscience experts today is that it is predicting. What is it predicting? The anticipated needs of the human organism in a very broad sense, not only anticipating the effects of the VUCA environment but also anticipating the natural necessities of our body and of our psychological and social needs. Continual predicting is presumably the result of an evolutionary advantage designed to help us prevent the decay and degenerative characteristic of all advanced biological systems. For example, it predicts the need for hydration by recognizing an internal signal as thirst. Undoubtedly, it is easy to understand the advantage of an anticipatory action of drinking water before entering deficit states of dehydration. A deferred reaction to drinking water when dehydrated would be counterproductive in terms of survival and evolution. The advantage of anticipating is evident in all areas, whether you anticipate the reaction of persons you interact with or simply predict, whether a dish is tasty or how long it will take to go to work. All those ceaseless and often trivial predictions serve the overriding purpose of keeping us alive and well.

So, how do brain and body realize and implement the anticipation of biological needs?

The principle that rules the anticipatory process is the minimization of energy, or what is called in computational neuroscience Free Energy. The field of computational neuroscience has its own terminology and for the sake of consistency and scientific rigor this workbook will stick to it. The term "minimizing" for example stems from underlying mathematical computations; it is used here as a short form for "reducing as much as possible" in everyday language.

Minimizing Free Energy allows individuals to stay within their biological and physical requirements for their self-organization and survival and to slow down decay and dissipation, which is the goal of brain activity (Friston & Stephan, 2007; Friston, 2009, 2010).

Technically, it is a theoretical informational quantity captured by the Free Energy Principle (FEP). In physics, energy is related to accomplishing a task. You could compare it, for example, to the energy necessary to move your car from A to B, let's say, from Zurich to Milan. Free Energy as an informational quantity is conceived as the adverse effects on an individual's whole being (in MBSAT terminology on the integral BETA comprising Body sensations, Emotional sensations, Thought processes, and Action impulses); it is the energy that is created from undesirable and unexpected states or situations, for example, when you enter a room and you experience difficulty breathing because of the unanticipated poor air quality of the room. It is a negative effect on our psychological, physical, and relational self, resulting from unexpected interactions with the changing and chaotic forces of Volatility, Uncertainty, Complexity, and Ambiguity (VUCA) in the environment. When we can minimize the adverse effects

of VUCA on our BETA, we are minimizing Free Energy, and it helps us flourish; it helps us thrive and become creative. However, when Free Energy is left unbounded instead of reducing it, it creates disappointing, demoralizing, and disintegrating states in our BETA. You can think of Free Energy as a chaotic and potentially destructive force that needs to be channeled and directed in constructive ways. This is what MBSAT training is about: MBSAT is a methodology to help us learn from the adverse effects of Free Energy, to domesticate and master it and lastly thrive in a VUCA world. Wrestling with Free Energy is an integral part of living and in the process we become resilient and resourceful.

An easy way to conceptualize the Free Energy principle is by looking at Figure 1.1. The mustang, a wild horse full of impetuous, untamed force, is an analogy for Free Energy. If his vehement nature is left unattended, it can seriously hurt you and cause great harm. However, if one is able to domesticate the horse, which is the equivalent of minimizing Free Energy, its strength and dynamism can be put to good use and become a valuable resource as the illustration shows.

According to Friston, the Free Energy Principle, it can take different forms, briefly described in the following paragraphs with an attempt to explain the concepts in an easy-to-understand manner. K. J. Friston is an outstanding neuroscientist and a pioneer of brain imaging who has dedicated his lifework to understanding how the human brain works.

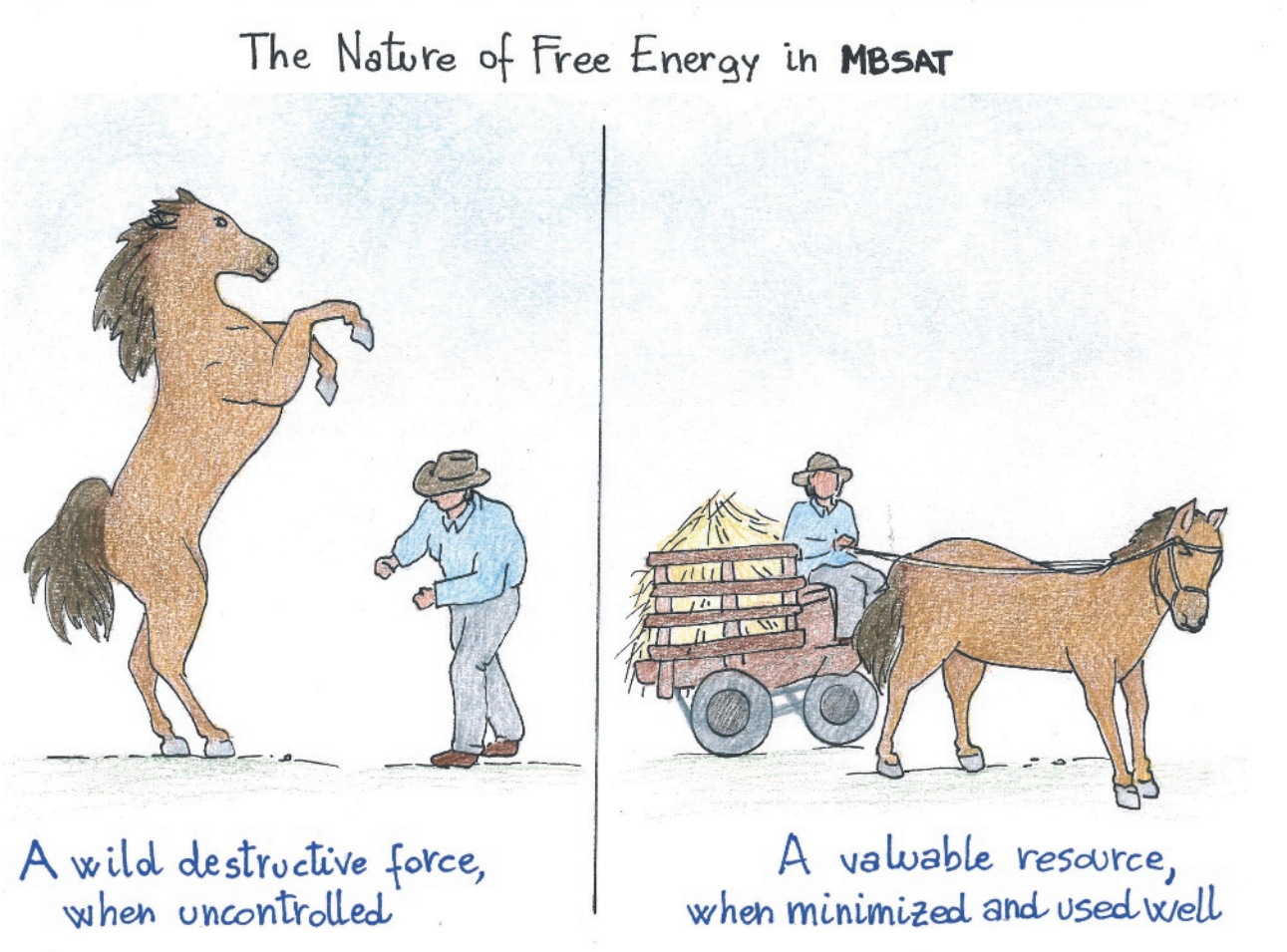

Figure 1.1 The Nature of Free Energy in MBSAT

1.2.1 Free Energy as posterior divergence

Free Energy can manifest itself as a posterior divergence, a difference between what one perceived while it was happening and the natural causes of the sensory generating an element of surprise, when the initial perception and the feedback from the environment diverge. For example, imagine that you hear a delicate piece of music with a wonderful violin playing, and you visualize a male musician with his instrument. You ask your friend about the musician who is playing, and she replies it is Hilary Hahn. To your surprise, she is a woman. "She plays wonderfully," you said to your friend. Ok, now you know, and you make a note internally to yourself that women can play the violin as well as men. You just updated your perceptual model of violin players to include women. Your brain model of violin players is now more complete, so next time you hear someone playing the violin, your perceptual inference (your anticipated judgment of who is playing) will include both women and men as possible musicians, which leads to fewer states of surprise. You will be less subject to surprise and, therefore, will minimize Free Energy. This is an example of how dealing with Free Energy can result in a gain. In the same way as Free Energy is an integral part of life, so are surprises. It all depends what we are capable to make of them.

1.2.2 Free Energy as prior divergence minus accuracy

Prior divergence implies a difference between your anticipated beliefs about the causes of what is happening in the world and the sensory data you then observe minus an element of accuracy. The more accurate the anticipation has been, the smaller the divergence and the more success in minimizing Free Energy. For example, you can imagine the following situation.

You are looking for a home address. As you know the area, you can quickly find the address and anticipate high accuracy levels. However, as you get close to your friend's house, you find traffic signs of rerouting because of road works, prompting you to make a long detour. You lose your orientation, as it compromises the accuracy of your prior belief about getting there; therefore, you are generating free energy. To correct the situation you drive more slowly, searching for street signs and house numbers until finally, you find the expected location. Here, losing your orientation (accuracy) led to your slowing the action of driving, which corresponds to reducing the complexity of the previous predictive actions and minimizing Free Energy in the process.

1.2.3 Free Energy as expected energy minus entropy

Free Energy can also be conceived as expected energy, which implies a generative model of the world in our brains corresponding to the joint probability of a sensation and its causes happening together, minus the entropy (disorder) that might affect recognizing the causes of the sensations.

Imagine having your teeth checked, and the dentist tells you need some new filling. She explains she could give you anesthesia to make it less painful. This will cause a numb feeling that will take about half a day to wear off, and you may also experience some difficulty when eating. Or she can repair the tooth without anesthesia, avoiding the inconvenient after-effects, yet it will be a bit painful during the half-

hour while she works on the tooth. You choose to go without. While the dentist is doing her work, you feel the pain (your sensation), but you have expected it because you were told about it. No surprise here, as in your brain generative model, "dental work without anesthesia" can indeed cause pain; therefore, knowing that is the fact, you can minimize Free Energy (surprise) and get over it relatively well. There is also no complexity; you are in a state of high accuracy and slowing down entropy, which is the only thing you can do in this situation. It is actually all we can do as humans in the long run. In the film *The Dark Tower*, Matthew McConaughey says to Idris Elba: "We both know that no matter who crosses the finish line first, the universe will die out of entropy. Death always wins, that's the deal". Yet, in the meantime, the purpose is to have a meaningful and flourishing life.

1.2.4 Minimizing Free Energy

As we can infer from these examples, minimizing adverse effects of the unexpected helps minimize Free Energy and vice versa. In MBSAT, when we speak of minimizing Free Energy (FE), it means reducing the adverse effects of VUCA. For practical purposes in MBSAT, FE can be conceived of as an unregulated, wild and potentially harmful energy as mentioned above and illustrated in Figure 1.1. By now you are probably also getting familiar with the term minimizing, used throughout this workbook as a synonym for "reducing as much as possible" in line with the terminology of computational neuroscience.

Here is another example from everyday life to make the concept of Free Energy as practical and hands-on as possible, while still rooted in and congruent with its highly scientific and theoretical foundations. Imagine going to your favorite Indian restaurant and ordering your favorite dishes. However, when the food is served, you notice it looks different, and when you taste it, you realize it is not as delicious as it used to be. You are disappointed and maybe upset. You take action by asking the waiter about what is happening. The waiter and the manager, who also approached, explain that there had been a policy change; they are now specializing in buffet and employed a new cook. Dishes ordered while sitting at a table are now part of the à-la-carte menu, and this is what the new cook is not so good at, the manager admits. Here, we can observe the Free Energy Principle in action. You predicted a state of satisfaction by deciding to eat at a place you know well and where you like the quality. By choosing your favorite restaurant, you expect to reduce VUCA. Still, now you find yourself in a state of dissatisfaction despite having made a careful prediction and a safe decision from your point of view by going to a risk-free restaurant with the prospect of low VUCA, enabling you to minimize Free Energy. The difference between the desirable predicted states you were expecting and the states of dissatisfaction you are now experiencing is a surprise. Whenever you are confronted with this kind of surprise or deficit, in whatever dimension it could be (a quantity, a direction, a magnitude, a certain quality, etc.), the Free-Energy Principle is at play, and the situation will obliterate more Free Energy than anticipated and desired. Therefore, to keep ourselves in a state of flourishing, one should always seek to minimize Free Energy. The goal of MBSAT is to build the strategic awareness and the adaptive skills needed to achieve this state of flourishing despite challenges and adversity.

Action and acting are essential components of the Free Energy Principle. Acting is what will help reduce total Free Energy by shaping the world around us. Action can comprise a perceptual change to minimize uncertainty (inquiring about the causes and knowing the causes of an event, such as the food not being to one's liking). With active adjustment of our beliefs, one increases the accuracy of expected events, in this case enjoying the expected tasty dishes by asking who is cooking today.

The example of the eating-out experience can also give additional insights. It shows amongst others that by minimizing Free Energy (VUCA), one is maximizing the evidence of one's prediction models; here, the belief was "eating my favorite dishes at my favorite Indian restaurant will give me a lot of satisfaction." Suppose the food conformed to your expectations, then you would have had the evidence for your prediction/ decision model: your "eating at my preferred restaurant" belief has been confirmed. However, because of the error in prediction (assuming the usual way of cooking, which proved mistaken), the belief turns out to be inaccurate.

Minimizing Free Energy by avoiding surprise and its adverse effects drives human life and functions as a unifying factor. It is a universal principle of perceiving, learning, acting, and conducting our lives. It not only shapes our existence but is also at the basis of how our institutions function and adjust and learn. Friston and Stephan (2007) suggest that Free Energy and the Free Energy Principle (FEP) are at the core of all human activities. For example, we can observe the FEP operating in one of contemporary life's most important cultural institutions: business organizations. The FEP and its functioning in the world of business merit a closer look.

In business, the overriding goal is profit: it determines the value of a company and is essential for its survival. Profits result from a simple equation: revenues less cost equal to profit (R–C = P). CEOs and managers responsible for for-profit centers are constantly seeking strategies to increase earnings by reducing the firm's cost structure, amongst other policies.

Surprise will be defined as any unexpected increase in the firm's cost structure or reduction of the revenue stream leading to lower profits, hence an undesirable outcome. Thus, business managers spend a significant amount of time and effort minimizing the magnitude and quantity of costs to build evidence for increased profits. This is a practical example of how the Free Energy Principle operates at the core of business settings.

One needs to appreciate that a manager who only minimizes costs will eventually compromise the future survival of the firm. To ensure revenues in the future, business leaders need to take actions that increase strategic costs by investing in new products, services, production capacity, etc., to stay competitive and guarantee the novelty of the company's offering. However, these particular types of strategic cost-increasing initiatives will naturally increase complexity and uncertainty (VUCA) in the business system. In evaluating the quality of decisions, CEOs or managers will need to maintain a cost function with a low average of predictions errors such as faulty products, poor services, unskillful choices, etc. Some mistakes are inevitable; the key is to stay within the optimal tolerance of prediction errors to maintain the organization's viability. This tolerance limit is called the upper bound

of the Free Energy Principle (FEP). It is a type of tipping point beyond which damage becomes very impactful, if not irreversible. However, most of the time, this upper bound limit cannot be quantified precisely, especially in VUCA, when information is incomplete and changing rapidly. To avoid hitting Free Energy's upper bound, companies strive to contain and track prediction errors with strategic plans and budgets.

The equivalent of a manager focusing solely on reducing costs and never investing would be a person who locks herself in a dark room to avoid surprises. Eventually, the pervasiveness of VUCA and entropy will catch up, compromising her physical existence as a living being (Friston et al., 2012; Clark, 2017). To prevent passing from active living to lethargy or even death (an adverse phase-transition in the terminology of FEP), she will need to allow herself some prediction errors to learn to adapt to the changing environment skillfully. This implies that she will need to invest some of her "surprise expenses budget" by testing and experimenting, thus implicitly accepting some unavoidable errors. Again, in doing so, she needs to maintain the average of her prediction errors below a certain upper threshold of Free Energy, as this is the only strategy that increases her survival chances and keeps her vital integrity. Living in constant change and uncertainty, any organism, whether human or institutional, must conserve its vital force by minimizing Free Energy to survive. As Friston and Klaas write: "The Free-Energy Principle can be motivated, simply, by noting that systems that minimize their Free Energy respond to environmental changes adaptively." (Friston & Stephan 2007, p. 9).

To better grasp the Free Energy Principle (FEP), we may think of our environment as everything around us. We live in an environment, but we are not the environment. We differ from plants, dogs, buildings, cars, etc., apart from more complex phenomena like organizations or processes. It is like having an invisible wall separating us from the "out there" (everything that is not me), what neuroscientist K. Friston calls a Markov blanket. Therefore, we are not directly influenced by what surrounds us, yet the environment affects us indirectly through our senses (our BETA in MBSAT language). We habitually distinguish between things we like and dislike and things to which we are indifferent. We influence the environment with our actions by changing things we don't like or creating things we do like, thus creating an existential loop.

The German philosophers W. Weise and T. Metzinger suggest the following experiment. Imagine making a list of essential things we need to survive, and another with things that endanger our survival. The result would be a concise list of the things we need for survival: air (which is free), food and water for internal energy, a place for resting (sleep), a partner for reproduction, and a few more items. The list of potentially dangerous things to our survival is almost endless. Eating the wrong plants can make us sick; a dog can bite and infect us with rabies; we can fall from a building; a car can hit us; the air can be contaminated; a friend can betray us; we can get divorced, lose our jobs, etc., etc. All of this is chaotic energy, suggesting that we need to minimize the impact of this energy on our lives to keep ourselves alive. That is the Free Energy Principle in a practical nutshell.

So, how can we achieve the vital aim of minimizing Free Energy? The following section explains how the brain helps us in doing so.

1.3 The Bayesian Hierarchical Hypothesis of the Brain: How the Brain Minimizes Free Energy

The term Bayesian has been coined in reference to the English statistician and religious minister Thomas Bayes who wrote a pathbreaking paper on probabilities in the 16th century. Later the French statistician Pierre-Simon Laplace expanded the idea that became known as Bayes Theorem. It suggests that with new information, one can update a prior held subjective belief about an event and develop a new, evidence-based updated belief. It is a statistical approach that encourages discovery and exploration, as a person can change her previously held beliefs and opinions as she gains new knowledge and learns about new realities. This is the mindset MBSAT strives to convey.

Bayes' Theorem uses three elements to revise the probability of an event. A subjective belief called "prior" is based on experience. Another feature represents the "likelihood" of something you believe you are sensing, given your prior belief. By adjusting the "prior" based on the "likelihood" of the event, you arrive at the "posterior" corresponding to a new belief based on new observations after having taken care of some of the likely outcomes.

To illustrate these elements, imagine the following situation: John, a business executive, needs to travel to join an important meeting. As part of the requirements for travel, he takes a COVID-19 test, and it comes back positive (the posterior). It surprises him, because he doesn't have symptoms and feels well and therefore hypothesized that he shouldn't have the virus (his prior). He calls his friend Reto, a physician, who tells him that the test is very reliable and that only 1% of the population in the city is infected. Still, there are errors, with healthy people sometimes getting false positives (a positive test result, although the person is not infected). "The issue is to know," says Reto, "if your case is in the 1% of the wrong diagnosis. I needn't go through the math, but I would say that you have about a fifty-to-fifty chance of having the virus. Take a second test (new information). If the result is positive, then you know you are infected."

The illustrations below recount the conversation between the business executive and the physician and present the underlying math (Figures 1.2 and 1.3).

In simple words, one begins with an initial belief and gathers fresh evidence to lead to a new belief. In a nutshell, this leads to the formula: new belief = old belief + evidence.

For mathematically interested readers Figure 1.3 presents the detailed calculations. Obviously, hardly anybody would actually do the math. Instead of thinking in probabilities, most people think in percentages or apply rule of thumb derived from sampling the environment. Thus, our brain, more than a Bayes calculation machine, is a sampler of experiences.

Figure 1.2 Bayesian Questioning Mindset in MBSAT (I)

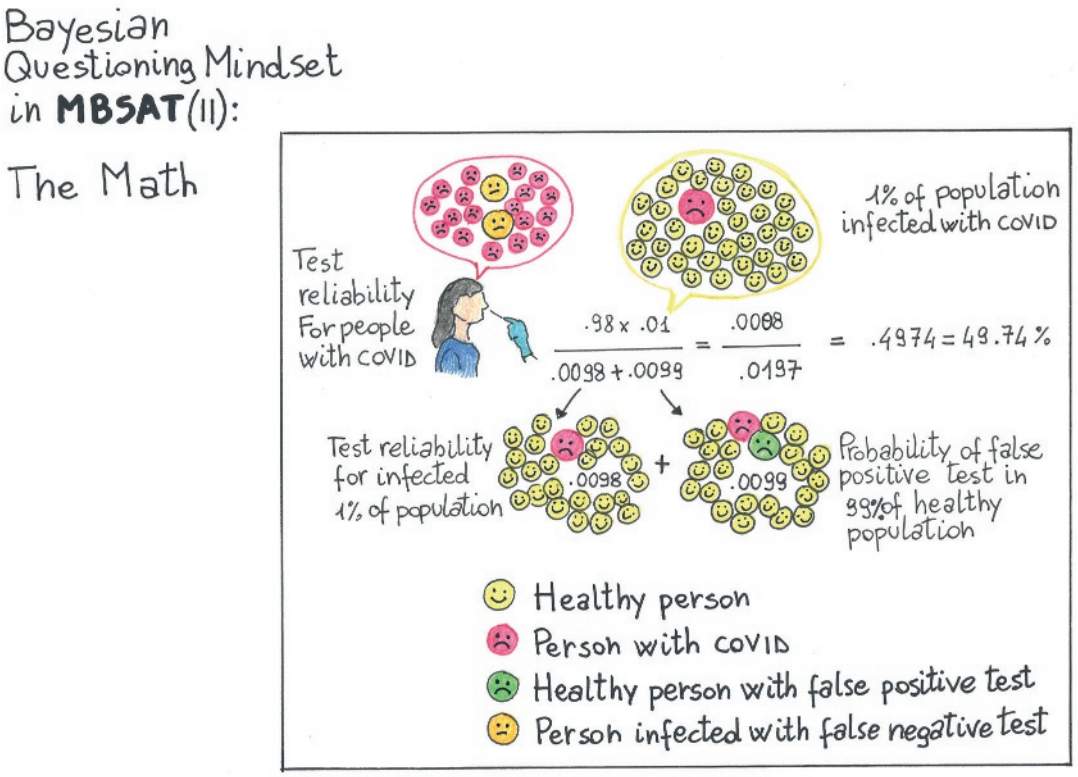

Figure 1.3 Bayesian Questioning Mindset: The Math (II)

Bayes formulations are data-driven models that have been crucial in developing and advancing modern Data Science. Amongst others, they are used extensively in Machine Learning, for example, when Netflix, Amazon, and many other online services collect data on their clients' preferences and use this information to recommend movies, books, and other products and services that they predict could be of interest for their clients. Similarly, spam systems in email programs also use Bayesian networks to classify emails as spam based on the user's prior experience. Emails sent to the trash are integrated into the learning process of the email program to recognize them in the future and send them directly to the trash bin, thus optimizing the users' email function. Self-driving cars use Bayesian predictive systems for calculating directions and regularly download satellite information for optimally updating and directing the autonomous vehicle towards destination points.

There are truly mind-boggling cases of machine learning. Google's DeepMind company developed a learning program they used to beat the Korean GO world master Lee Sedol; it was based on Bayesian Learning, using two learning algorithms to determine how helpful a move could be and another to choose actions. The playing program AlphaGo learned the moves from its opponent and updated its data bank to develop unexpected new moves, beating master Sedol four times out of five games.

At Harvard, I was lucky to study two semesters on Decision and Negotiation Analysis with the late famed Prof. Howard Raiffa who was a pioneer Bayesian statistician and the father of decision analysis. He taught us to maintain our beliefs flexible to update them when new information becomes available during negotiations. This flexibility of beliefs is now more critical than ever in times of VUCA.

1.4 The Relation Between the Brain and Bayes Theorem

As mentioned above, there is increasing consensus amongst neuroscientists that the brain is not reacting but is in the business of anticipating and making predictions about our needs to accommodate, adapt and improve people's survival opportunities in the changing VUCA environment. The critical question is, how does it do it?

The brief comment about Bayes Theorem in the preceding section presented a natural description of how Bayes' idea is used for inferring and predicting causes of phenomena, based on beliefs that can be updated with new evidence to formulate new beliefs and predictions. The Bayesian Hierarchical Brain Hypothesis in neuroscience suggests that the brain operates similarly. As we live in a VUCA world, there is no possibility of knowing all the causes of the phenomena we confront. The solution for the brain is to function as a chief prediction officer (CPO) based on prior experiences and beliefs. The brain has developed a mechanism that simply anticipates and predicts needs based on previous experiences and beliefs. As it receives new information through the senses, it either validates its predictions or updates the brain with new beliefs.

What entails this idea of a Bayesian Brain (BB)? "Bayesian Brain says that we are trying to infer the causes of our sensations based on a generative model of the world… If the Brain is making

inferences about the causes of its sensations then it must have a model of the causal relationships (connections) among (hidden) states of the world that cause sensory input… It (the BB) provides a principled explanation for self-organization in the face of a natural tendency to disorder… A self-organizing system that minimizes its entropy (disorder) would appear to be making Bayesian inferences about its sensory exchanges with the environment, which of course, is just the Bayesian brain hypothesis." (Friston, 2012b, p. 1233). For the BB hypothesis, humans perceive reality under an implicit mechanism that looks similar to the principles underlying Bayesian inference, the statistical method explained above that has become very popular with data scientists. An example may help illustrate this reasoning.

Imagine that it is midnight, and you are in deep sleep. Suddenly, there is a knock on your door. You and your spouse wake up, go to the door and look out, but see nothing. Both of you wonder what it could be. You believe that someone is trying to rob you, as you remember that a neighbor was robbed a couple of weeks ago; your spouse believes that it is maybe someone in distress who needs help. Both decide that it is safer not to open the door and to abstain from finding out the cause of the knock in the middle of the night. The following day, as you pick up your mail in front of your house, your neighbor asks you, if you heard a knock last night. She tells you she also heard the knock and opened the door after talking to her husband. She found Mark, another neighbor, collapsed and suffering from a heart attack on her doorstep. They rushed him to the emergency and fortunately he is doing well now. This chain of events shows you a BB in action. The knock on the door is the initial event. A discussion about the likelihood of the cause followed it: depending on the weight or veracity one puts into a belief one can formulate different priors: a robbery attempt or a distress call. After gaining more data through the neighbor, the actual cause of the knock is revealed, namely an emergency call by another neighbor. This information now allows building the posterior.

Bayesian neuroscientists assert that this is the way our brains always work. The process relies on a generative model that has developed from prior experiences and generates inferences about the causes of phenomena and adaptive behavior patterns. Given that the brain is inside the skull, it has only access to phenomena through the senses; therefore, it is constrained to infer the causes of events (Ramstead et al., 2019). It has a de facto veil that separates it from the environment in the same way as the door in the example above separates the couple from the actual cause of the knock.

Thus, what the brain does non-stop is actively inferring about what is happening, with some subjective appreciation of trueness or falsehood about the causes, and evaluating and selecting adaptive actions to maintain viability in relation to proven states of survival. The brain is permanently inferring, thus seeking verification for our hypothesis (beliefs) to reduce prediction errors and free energy.

Here are some practical examples to further explain this process.

- You go to the office in the morning and notice your boss in the parking lot. You greet her in a friendly way; she answers back laconically and instantly turns away from you. "What is the matter?" you ask

yourself. "Have I done something wrong? Or are there plans to fire me, given the difficult situation of the company?" These kinds of thoughts cross your mind. Only late in the afternoon you hear from a colleague that your boss has severe personal, non-work-related difficulties. Now you relax after spending most of the day worrying, wasting a lot of Free Energy on unnecessary apprehension.

- A manager sends an email with an attractive offer to one of the company's best customers. She hears nothing in return. Even after several more emails, still no response. She gives up, believing that the client bought the product from the competition. Only weeks later, she receives a message from the client, excusing himself for not responding earlier. He explains he has been in hospital in intensive care, fighting a COVID-19 infection. Now that he is back, he wants to set up an online meeting and discuss the offer.

The hidden causes of these situations (the terse response of your boss and the lack of response from the client) were resolved in retrospect after gaining clarity about the causes of events: family issues in the boss's case and COVID-19 in the client's case. The initial predictions were erroneous; only after sampling additional data were the individuals able to formulate new predictions ("Actually, I am not getting fired"; "I can still close a deal"). This is precisely what the brain has in common with Bayes Theorem: revising personal predictions after having sampled new information, thus moving from an initial subjective prior to a data-driven posterior. Ambiguous situations such as the illustrations above abound in daily life, often leading to errors in inferences that consume energy and create stress and unhappiness as the causes of the events remain uncertain. This makes it very hard to minimize Free Energy.

Of course the brain, as already mentioned, doesn't do these calculations in an explicit Bayesian statistical sense, but samples a couple of causes of an event. In the case of the knock on the door, the couple sampled two possibilities: some thief in front of the door or someone in distress; there could be more possible causes, but clearly, the couple couldn't represent all causes given the constraints of time, processing capacity and bounded rationality (Simon, 1991), so they settled on two possibilities each with an implicit probability. "The brain represents information probabilistically, by coding and computing with probability density functions or approximations to probability density functions." Knill and Pouget, (2004, p. 713). Simply put, this means that the reality from which we extract information to manage our life is not black and white but resembles a continuum of grey tones in an uncertain, changing, and ample VUCA space. Therefore, the best we can do is to hold helpful beliefs about the causes of reality that allow us to build good predictions as the basis of skillful decision-making (should they open their door, yes or no). And this is the Bayesian Hierarchical Brain in action. It is hierarchical because the sensory data move hierarchically from the bottom up to higher levels of cortical structures, moving sensory inputs that are then validated at each level of the cortical hierarchy. In the opposite direction it carries information as predictions, generated internally at the higher level of the cortical structures and validated at each level as they move down the sensory hierarchy. Messages pass through a cortical hierarchy in a bi-directional sense.

All this happens in split seconds. The brain with its billions of neurons that communicate at lightning-speed is a true marvel.

1.5 The Models in the Brain and Active Inference

The question, then, is how our beliefs about the causes of our sensations come about. Friston asserts as we have seen in the quote above (above Section 1.4; Friston, 2012b, p. 1233) that the brain is inferring the causes of our sensations based on a generative model of the world.

1.5.1 The brain models

Brain models are, in fact, a cluster of meanings of the things we perceive and show different values that an event can take. It relates values to decision-making; things we value trigger a decision to act and accomplish them; if we don't value certain things, we tend not to decide on them. In the example of the knock on the door, we can see that the wife and her husband attached different beliefs to the cause; thus, each of them had another value encoded in their BM concerning the event "knock on the door," but after coordinating their variational inferences they decided not to act on the signal, deciding not to open the door.

The make-up of the brain models is based on two mechanisms. One, based on experiences and beliefs about possible causes of an event and generating predictions, are the so-called Generative Models (GM); a second mechanism that observes data and recognizes causes of events is called the Recognition Models (RM).

Brain models are "a mathematical abstraction, comprising two related networks of mathematically modeled 'neurons.' One, the recognition network, works from the bottom up; it's trained on real data and represents them in terms of a set of hidden variables. The other, a top-down 'generative' network, creates values based on beliefs of hidden variables. The training process uses a learning algorithm to change the structure of the two networks to classify the data accurately. The two networks are changed alternately, a procedure known as a wake-sleep algorithm". (Stewart, 2019, p. 194) To better understand the interaction of these networks, let us contemplate Figure 1.4 Active Inference for Decisions – AID in Daily Life.

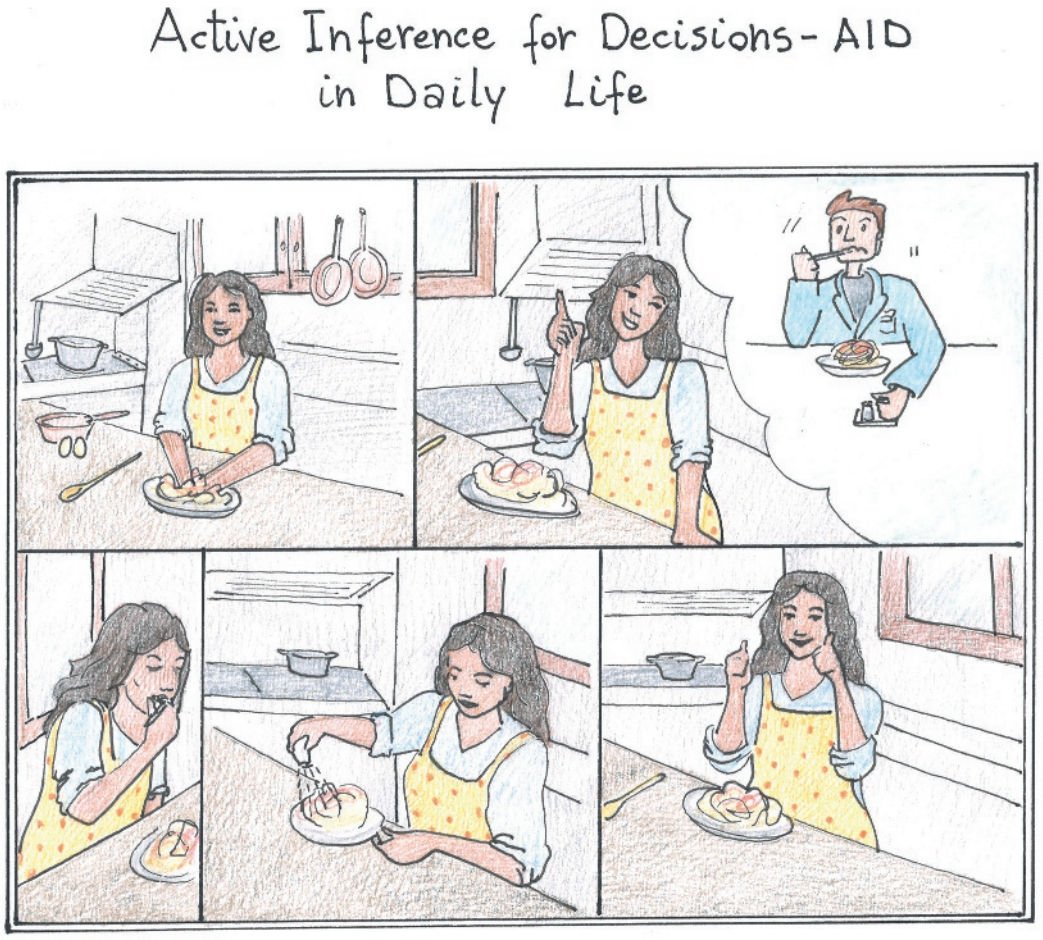

Figure 1.4 Active Inference for Decisions (AID) in Daily Life

It depicts the mechanics of the brain models, using an everyday example. A stay-at-home parent is cooking dinner for her family, the same dish she has already prepared several times before. Based on her generative model, she prepared a dish she believes will be appreciated by her family. While preparing the food, she predicts having a nice dinner with her husband (the generative model); to reduce Free Energy she tastes the dish to make sure it is well seasoned (the recognition model), makes some adjustments, and decides the dish is now ready to be served. In that scene, we witness the Bayesian brain in action: the generative models (generating several hypotheses about the desirability of the dish, the level of spice, etc.) and the recognizing models (tasting the dishes). She has used two strategies of Active Inference:

a) She used her perception skills to optimize the bound of surprise (avoiding generating Free Energy) by choosing a dish that she knows her family likes (her prior).
b) She takes actions (tasting the dish) to minimize the bound of surprise (her family complaining about the flavor of the dish). Her surprise would be the family not liking the dish.

The contrary (her family enjoying the dish), will provide evidence that her models worked, thus, she has minimized Free Energy.

Brain models have additional characteristics; in particular, they are dynamic and hierarchical (above Section 1.4), (Badcock et al., 2019a and Badcock et al., 2019b). The term "hierarchical" calls for clarification in this context, as "hierarchy" can have an adverse connotation. For example, in inefficient public administration there is usually an accumulation of socio-political power in the political sphere at the highest level of governmental hierarchy. Yet the case of the hierarchical Bayesian Brain is very different. It resembles more the political structure of a well-functioning democracy that works as a dynamic distributed hierarchy where ministers will share their specialized knowledge in a collective decision-making process, resulting joint decisions to the benefit of their citizens. Similarly, a hierarchical brain works to optimize and coordinate the work of the different hierarchies of the brain for efficient survival outcomes for the individuals.

1.5.2 Active Inference (AI)

Based on what we have discussed so far, we found out that the brain is an embodied organ acting on a Bayesian principle, inferring the causes of sensory perceptions. Now, we need to know how the Bayesian process is implemented.

Within Bayesian Cognitive Science there are several models on how the brain formulates inferences (Spratling, 2017), for example, Predictive Coding (Rao & Ballard, 1999), Predictive Processing - PP (Clark, 2016), Prediction Error Minimization - PEM (Hohwy, 2013) and Active Inference (Friston et al., 2017). What all scientific approaches have in common is the centrality of generative and recognition models as mentioned above. They also all share the same view of the primary functioning mechanism of brain activity, a process that allows us to articulate a new belief following the pattern "new belief = old belief + new evidence."

It is Active Inference (AI), a process that better fits today's postmodern active life. It argues that individuals do act on their predictions where internal states don't match the hidden external causes by acting to close the gap, thus actively minding prediction errors and minimizing Free Energy. We not only update inferences to adapt our brain models to the world, but even more essential, we take actions to change the environment itself.

Thus, AI's pragmatic orientation makes it significant, attractive, and relevant. The aspiration to minimize Free Energy is the source of the many wonders and advances we have in our lives. Cars, planes, houses, air conditioners, tablets, smart phones, computers, chairs, accounting information systems, consulting services, marketing plans, medical devices, cashmere jackets, watches, books, Facebook, Google, Wikipedia; almost everything we experience in our living niche follows the Free Energy Principle – FEP and the enaction of AI. These artifacts have been created by humankind's work as extended, enacted possibilities to minimize Free Energy in our quotidian lives. I see AI as a liberating mechanism, meaning it does not leave us to the hazard of a random destiny, but we can actively engage in building our present and future. AI provides the tool for how individuals can satisfy the elements of the Self-Determination Theory (SDT) of motivation: the need for autonomy, relations, and mastery. If Active Inference is correct, we can gain personal agency as autonomous beings and self-determine the direction of our lives, mastering not only ourselves but also masterfully acting to shape our eco-niche to our advantage.

The mathematical neuroscience principle of Free Energy offers to a world full of political, social, economic, and environmental challenges the scientific motivation to engage in the changes we need to survive as a species.

So, let's unpack Active Inference to understand its functional and integrative mechanics. We can conceive of Active Inference as a computational process of Mind Learning similar to Machine Learning for silicon systems. It involves four states (Ramstead et al., 2019):

- **Internal states** (experiences, ideas, feelings, physical aches, amongst others) corresponding mostly to beliefs about the external states affecting by sensory states.
- **Sensory states**, our perceptions through our senses: what we hear, smell, see, touch, physically feel in our body when experiencing the external states.
- **Active states** correspond to the experience of the body in the physical space: whether it is moving or static, and the internal physiological movements of our body, doing things. Also at the level of simple mental action, acting virtually in the mind.
- **External states** include everything that is not an internal state, such as other people, material artifacts, and natural phenomena.

The illustration below visualizes the four states involved in Active Inference (Figure 1.5).

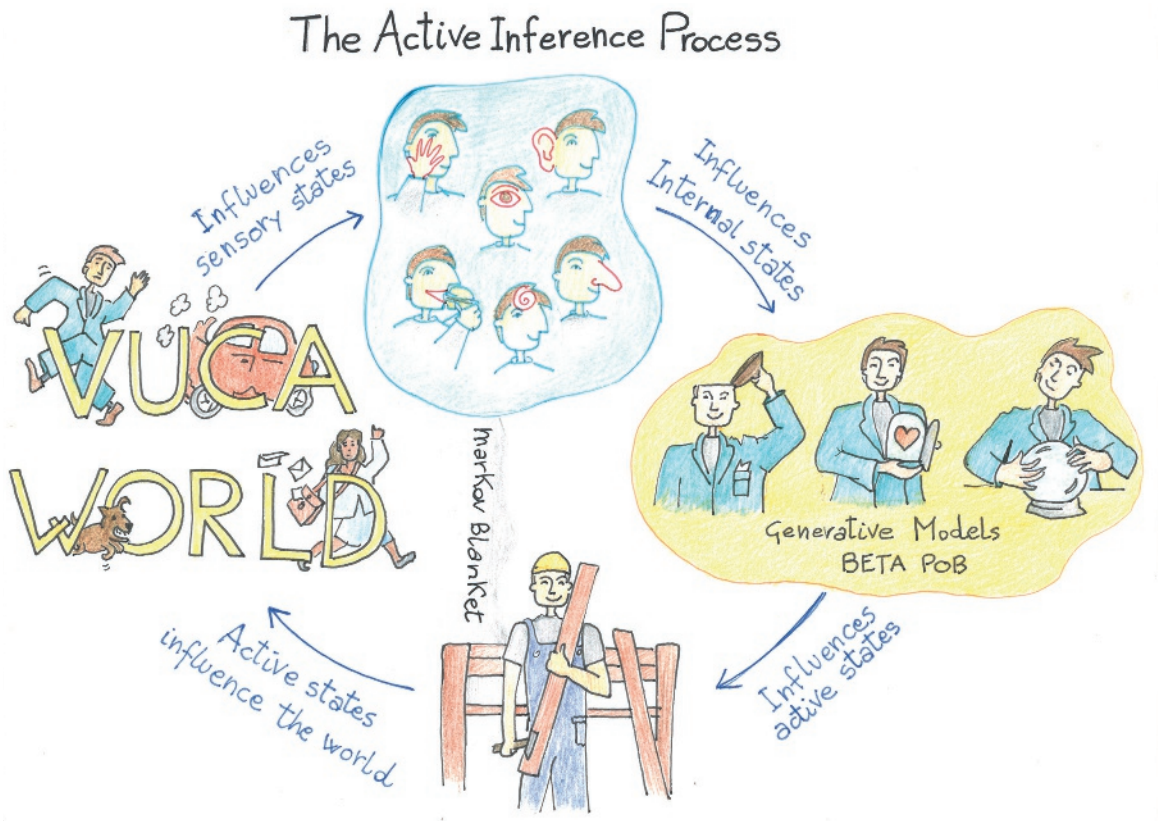

Figure 1.5 The Active Inference Process

In Figure 1.5 we see a veil, the Markov Blanket, separating internal states from external ones, accessible only through sensations and actions. The brain has no direct access to causes of events in the outer world, but only indirectly through sensations or actions of the agent, the individual. This indirectness is an additional source of VUCA, which is why MBSAT focuses on training individuals' sensations and actions to help them minimize Free Energy.

Active Inference happens at three levels of complexity and context to coordinate behavior for achieving desired outcomes and goals. The first level activates simple motivational processes. This is the case in the following sequence: you walk in the street and see a person wearing a nice jacket. Minutes later, you pass by a shop and see a beautiful jacket in the window. You go inside and buy the jacket. The appealing look of the person you saw before builds a motivating action to acquire the jacket based on a simple prediction: "With this jacket, I will look as good as that person."

The intermediate level corresponds to a semantic aspect based on beliefs prevalent in culture. For example, you are on the intercity train during the rush hour. An older adult gets on at the next stop, and you offer your seat as the train is full. Deferring to an older person is a universal courtesy rule. Therefore, you are predicting the person will accept the offer without offense and in conformity to the rules of society.

Finally, the highest level of complexity is determined by episodic or subjective beliefs connected to specific circumstances. Imagine, for example, that the person buying the jacket mentioned above lives on a restricted budget and is having second thoughts after the purchase. He is thinking about returning the item, when he remembers he will soon get his year-end cash bonus. This private episodic event outweighs his misgivings about getting the jacket, so he keeps it.

The three levels work interactively. In the example above, a higher-level episodic event - the prediction about getting the bonus - provides support to the first level motivation - the prediction of looking good in the new jacket - and also to the intermediate-level, generalized idea that he will look good in the jacket according to the fashions of the moment. (Pezzulo et al., 2018)

Under the AI scheme, the internal states are separated by a veil (Kirchhoff et al., 2018) from the external states, the former being only accessible through the sensory states and actions, which is the reason it is so essential to maintain steady and healthy internal states, as they are fundamental for keeping skillful generative and recognition models.

So far, we have discussed the computational aspect of the FEP corresponding to optimizing variational Free Energy by minimizing VUCA and its algorithmic character, corresponding to the rules behind the process of Active Inference. We now turn to how the Bayesian brain (BB) implements Active Inference (AI). Here, we will not engage in the neurobiological details of its implementation as that is beyond the book's scope. Instead, the aim is to provide an easily understandable explanation of how BB implements AI.

1.6 How the Bayesian Brain Implements Active Inference

For John R. Searle, the UC Berkeley philosopher of the mind, one of the chief functions of the mind is to relate individuals to the world by perception and action. As he writes, "by perception we take in information about the world, we then coordinate this information both consciously and unconsciously, and make decisions or otherwise form intention, which results in actions by way of which we cope with the world." (Searle, 2004, p. 179) The ability to see, hear, smell, touch, and taste lets us become aware through our senses. Perception for the empiricists comprises the raw data received by the senses; for rationalists, they add thinking to the sensory input to make sense of the percept.

In AI, perception works in reverse: the brain models predictions. "Perception is indeed a process in which we (or rather, various parts of our brain) try to guess what is out there, using the incoming signal more to tune and enhancing the guessing… the ongoing process of perceiving… is a matter of the brain using stored knowledge to predict, in a progressively more refined manner…" (Clark, 2016, p. 27) This is actually not a very recent view. As early as in the late 1980s, the British neuroscientist R. L. Gregory conceived of perceptions as hypotheses, percepts containing predictive power (Gregory, 1980). Therefore, in the scheme of AI, perceptions are predictions; they are perceptual guesses or hypotheses.

AI comprises three elements:

- Prediction
- Prediction Errors
- Precision

These elements are called the three Ps in this Workbook.

1.6.1 Prediction

Dictionaries typically define a prediction as a statement of what you think will happen in the future. In AI, predictions are expected packets of information that carry embedded beliefs, prior experiences, and an appreciation of the context of the perceived situation. They are sent down the neuro-cortical pathways of the brain with our best assumptions about the causes of the perceived phenomenon (a person's behavior, the impact of a dish we taste or a surface we touch, etc.). L. F. Barrett explains the process as follows: "We think of predictions as statements about the future, like 'It is going to rain tomorrow.' or: 'The Red Sox will win the World Series' …but here I am focusing on predictions at the microscopic scale as millions of neurons talk to one another. These neural conversations try to anticipate every fragment of sight, sound, smell, taste, and touch that you will experience and every action that you will take. These predictions are your brain's best guesses of what's going on in the world around you and how to deal with it to keep you alive and well." (2017, p. 59)

In AI, predictions are brain activities and can cover a wide range of dimensions. Concerning time, they can range from micro-moments to long timelines, all in the service of anticipating our needs to resist entropy and help us survive (minimizing Free Energy). As we commented before, AI can also take the form of epi-

sodic predictions. The focus is on a specific event concerning us personally, for example, predicting the outcome of a friend's dinner invitation. On other occasions, it can be more semantic, that is more about the general future situation in the world, such as predictions about the development of the economy and your company's finances. Usually, it will be a combination of both; for instance, your prediction might be about your company's future (semantic) and how it will affect you personally (episodic).

In a previous book (Young, 2017), I wrote about my first and only experience watching a live football game. It was in Madrid's famous Santiago Bernabéu Stadium, and despite not being a football fan, I became mesmerized by Ronaldo's play. In that match, he alone scored all the winning goals for his team. What I found fascinating was his way of playing. Often he moved in the opposite direction to where the ball was going, while most players were following the ball. Ronaldo repeatedly stood in the middle of the field just observing, like taking a rest and pondering; then, suddenly, he would bolt in the opposite direction to his team, only to see the course of the game changing in his direction with him already in an optimal position and able to catch the ball and score a goal. That game stayed with me for a long time. Finally, while writing my first book, I made the connection and realized that this was prediction at its best. Ronaldo is simply a supreme predictor. He has the natural abilities combined with trained skills and many years of experience playing the game, thus having enough statistical data at his disposal to make accurate inferences about the ball's movement. The secret of his success was being more precise in the quality of his predictions about the ball's movements compared to the other players. This insight allowed me to see the world differently and to look at successful people (managers, tennis or golf players, successful parents, teachers, or medical doctors, to name just a few) as individuals who are on average more precise in the formulation and implementation of their predictions than the mean of the population. Therefore, they have a low average of predictive errors in their life and can flourish, given that we could conceive a flourishing life as one with a low level of prediction errors.

To become good predictors, we need to understand how predictions come about. In AI, predictions are driven by priors corresponding to beliefs, a kind of deeply ingrained assumptions or convictions.

There are several types of such prior beliefs. Zeki and Chén (2020) define two forms of priors:

a) Inherited (biological) priors result from firmly held notions we are born with and are resistant to change even with extensive experience. They can have an evolutionary origin. For example, it is clear to everybody that we cannot survive without oxygen beyond a relatively short time. Trying to stay underwater for more than a few minutes will seriously compromise our physiological state; our body will enter a state of surprise (shock), and we cannot minimize Free Energy. So most humans have a prior belief that it is not possible to survive more than approximately 3 minutes underwater without breathing gear.

b) The second type of beliefs are gained (artefactual or synthetic) priors. They are based on concepts formulated postnatally and changed by experience through life. Some authors call them empirical beliefs and relate them to the hidden causes of events (Ramstead et al., 2020). These priors are less constrained than biological beliefs. An example could be the prior belief that Latin Americans are better dancers than Europeans, although there is no solid statistical evidence of this. An important aspect is that this

type of priors is influenced by moods, which are considered hyper-priors in the scheme of AI. For example, a person with a mood disorder such as depression generates pessimistic predictions that involve a high level of Free Energy, rendering it almost impossible to minimize it. (Badcock et al., 2017)

There is an additional distinction based on the focus of a prediction:

- Proprioceptive predictions have to do with generating actions, moving our body.
- Interoceptive predictions are concerned with emotional processing.
- Perceptions about the external world informed Exteroceptive predictions.

Figure 1.6 illustrates these three modalities of predictions. In the first case Misty Copeland, a principal ballet dancer in a famous ballet ensemble performing with her body proprioceptive predictions; the following figure represents a woman's interoceptive prediction of her probable state of pregnancy and the last is Megan Rapinoe predicting the movement and direction of the soccer ball.

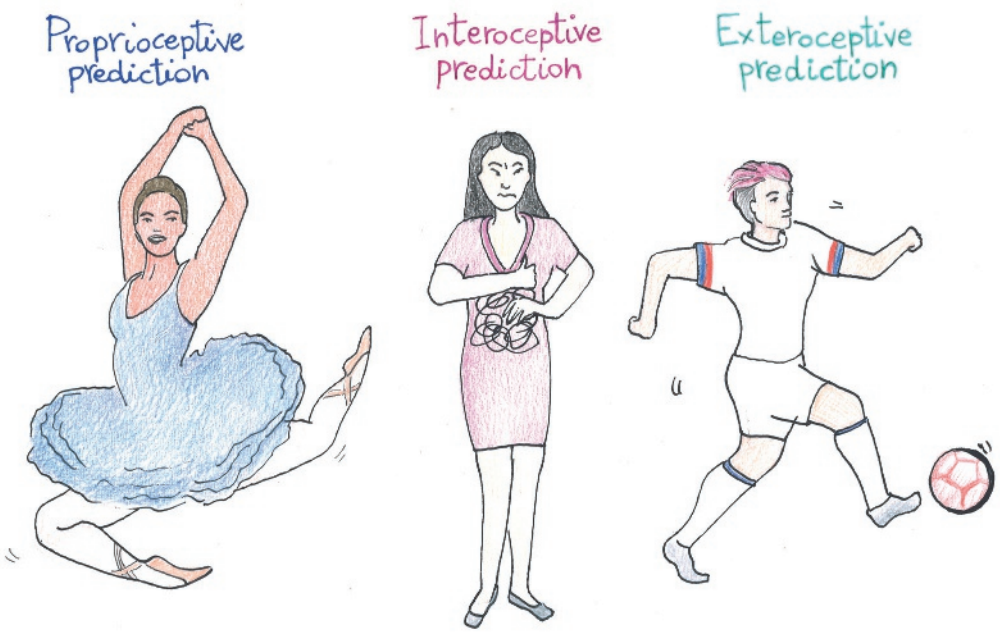

Figure 1.6 Proprio-, Intero- and Exteroceptive Prediction
(Adapted from Seth & Friston, 2016: Active interoceptive Inference and the Emotional Brain)

The second part of this book will comment on these predictions in more detail.

1.6.2 Prediction Errors (PEs)

The Bayesian Brain's generative models use prior beliefs about sensations and causes of phenomena to generate predictions and then test them against the environment's inputs, using the recognition models in a directional and hierarchical process. Discrepancies between the two signals imply that there must be some kind of prediction error (Clark et al., 2018).

Predictions come with "noise"; they can be warped, blurred, or distorted to various degrees because of the hidden causes of the object of perception. In addition, the internal states of the perceiver can also

affect the precision of the inferring data. The juxtaposition of perception, action, precision, complexity and the situation's context-sensitivity lets prediction errors emerge and creates surprise, an impediment to minimizing Free Energy (Hohwy 2013, p. 92). However, when these factors are skillfully combined, they can enable the minimization of predictive errors in a particular situation.

Some years ago, one of my daughters called and told me she was about to visit me, adding that she was not coming alone. "So, you're coming with your boyfriend!" I replied. "Nice! You can have your room as always. He is welcome, too." "Well," she said, "the thing is: it is not 'he' but 'she.'" "Oh, ok," I said, "no problem, come with her then." Over the years, she kept telling me how precious and vital my spontaneous response was to her. Although my internal world model led me to think of a couple as a man and a woman, I gave her a supportive response on the spot. I realized my predictive error only when she told me that her partner was a woman. My daughter's input prompted the error recognition, thus stemming from an external source and not from my reasoning. Had I insisted on the conservative, culturally driven "classical pair prior," I would have been delusional and certainly inflicted a lot of pain on my daughter.

The external world kept predictions in this account in check. Prediction errors (PEs) are the way of telling the brain that something is out of sync. PEs often occur when we try to predict fast-changing modalities in the world (for example, the new fluid concept of a pair). Our generative brain can also attempt to predict slowly changing conditions of the world (such as moving toward legalizing marriage based on a fluid concept of pairs). Here, the long-term neural connections in the brain are affected by synaptic efficacy (Hohwy, 2013).

PEs have several functions:

a) They help support perceptual inferences, as they are based on our guess about a percept/object and can be conceived as a measure of the appropriateness of our beliefs.
b) PEs can serve as red flags about the unexpected. For example, one can drive a car on a very familiar route while remaining alert to eventualities, such as children crossing the street.
c) Overall, PEs foster learning processes by integrating new data in our brain models, thus shaping our perception, attention, and motivation, ultimately shaping our beliefs and models of the world.

There are also several types of PEs. Perceptual PEs comprise errors in the sensorial channel: seeing, hearing, etc. I might, for example, swear that I saw a red cat, but it was, in fact, a brown cat. Cognitive PEs are errors in our mental elaborations. A case in point is the example mentioned above in connection with divergence (above Section 1.2.1), related to the erroneous assumption that the unseen violin player must be a man, as women cannot be such outstanding musicians. These two types of PEs are called unsigned or neutral in neuroscience, meaning they just report the surprise concerning the issue.

In contrast, the third type of PE is motivational and shows the valence of the error (big or small surprise). The motivational value stems from surprises creating a powerful motivation to learn. We prefer to avoid the unexpected, such as realizing that it was a big mistake not acknowledging that women can be consummate violinists. (den Ouden et al. 2012)

Rather than eliminating PEs, the realistic goal is to reduce them, which can be seen as a mechanism for minimizing perceptual divergence, the difference between our hypothesis about the object of our perception and the natural causes of the percept, for example, my instant assumption that my daughter's companion was a man versus the real hidden cause, the reality that her companion, unbeknownst to me, was a woman.

However, PEs are not just nuisances; they have functions as mentioned above. We need PEs; without them, nothing would surprise us or appear to us as novel; therefore, we would miss the opportunities for the brain to learn new stuff. In other words, errors are not all negative; they are part of our lives, but the fact remains that there is no use to produce errors on purpose. Some will happen anyway; so it is better to limit them as much as possible and when they happen all the same, the point is to make the best of them with strategic awareness and a well aligned BETA.

The trick is how to keep the average of PEs under a certain limit to minimize Free Energy, which makes the difference between having a hard time or flourishing in life. As people get into adulthood, their predictions tend not to be far off; otherwise, we would hallucinate. Feldman Barrett (2017) defines prediction loops as billions of tiny predictions and errors, like small droplets that join with other predictive loops in different brain regions. In her words: "The multitudes of predictive loops run in a massive parallel process that continues nonstop for your whole life, creating sights, sounds, smells, tastes, and touches that make your experience and dictate your actions." (2018, p. 63)

Figure 1.7 exemplifies the structural dynamics of a prediction loop.

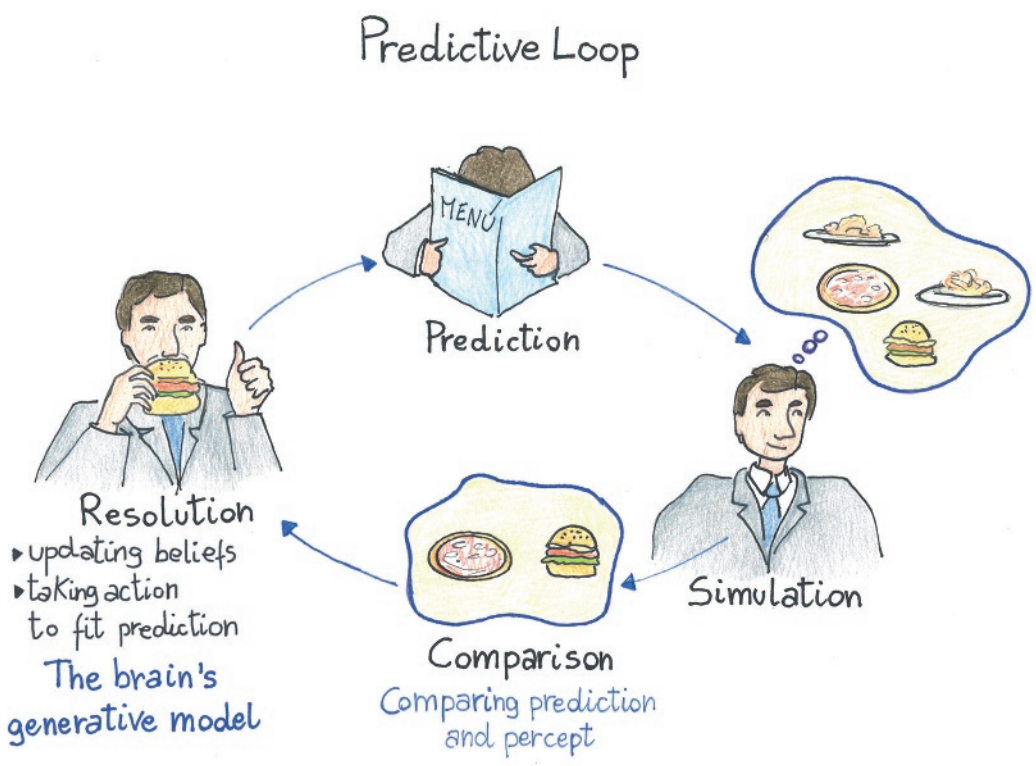

Figure 1.7 Predictive Loop

The prediction generates a simulation of sensations and actions compared to actual sensory inputs from the world. If they match, the prediction is confirmed, and the simulation becomes an adaptive experience; if not, it turns out to be a prediction error that needs to be resolved either by updating the generative model or by taking action to conform to the outer reality to the prediction.

1.6.3 The Precision of Prediction

Whether a prediction is precise is defined by the outcome in the real world. Hence it is not a mathematically exact quantity, but an approximation. In essence, you need to achieve an acceptable average of precision and keep outliers on the negative side (the variance) within certain limits to avoid major disasters.

Imagine you are driving and about to turn into a one-way street to the right. You stop at the corner and check to your left and in front of you. As you see that the path ahead is clear, you speed up and immediately hit the brake again in shock as you just barely can avoid a collision with a bicycle coming from the right side. You made a prediction error that could have had grave consequences. You assumed that the one-way rule is for all traffic and overlooked that the signals allow bicycle traffic in both directions.

In the framework of FE and AI, your oversight reflects a lack of precision in your prediction, resulting in a prediction error (PE). Given the interactive nature of this event, it must be added that the bicycle rider also made some PEs. He predicted that the car driver would stop and give him priority passage; however, he could have exercised some caution given the odd situation of the street with car traffic one way only, but bicycles allowed in both directions.

This is a case of socially constructed PEs, because of a lack of prediction precision from both the car and bicycle driver. In today's postmodern world of ubiquitous fake news, alternative facts, and media misinformation that, as some suggest, capture our attention to exploit our vulnerabilities, PEs are easily created ("I bought this product predicting it would make me happy as the commercials insinuated, but it is not the case and I ended up feeling disappointed"). What we need is a mediating element that helps reduce PEs. This is what makes precision about predictions so crucially important.

In the world of Active Inference (AI), predictions are generated by our internal model of the world; thus, implementing precision requires us to engage in another prediction process, which is the prediction about the accuracy of the prediction. It is a second-order type of prediction. First, the prediction (belief) regarding the phenomena gets created, and to reduce the possibility of PEs, we make a second prediction about the precision of the prediction (PP). AI's brain models will draw inferences from a probability distribution about the external phenomena and a second inference drawn from the probability distribution of the precision about the likelihood of the events based on observations.

To illustrate this, let us go back to the example above. The car driver's prediction is: No traffic, therefore move. The second prediction on the precision of the original prediction is: How sure is it that it is ok to move forward? Well, yes, it is ok to move, is the brain model's implicit answer, there is the one-way

traffic signal on the right, no one is coming from the left and the front, and clearly, no one will come from the right. The first prediction corresponds to object awareness, and the second prediction is a meta-awareness that comprehends the quality of the precision of the predicted phenomena. "To optimize prediction error minimization, we need to learn about and predict precisions. This means predicting when, given the context, a prediction error signal is likely to be precise. It is a kind of second-order perceptual inference because it is an inference about perceptual inference." (Hohwy, 2013, p. 65) "The prediction error depends on the precision of the prediction, and the actual observation… orthogonal to the precision of the prediction is the precision of the prediction error.... Here it is important to recognize two sources of precision, the precision of the prediction and the precision of the prediction error; … whereas the precision of the prediction is a measure of the amount of uncertainty regarding the prediction, the precision of the prediction error is a measure of the uncertainty; that is, whether it is reducible (can be decreased by learning) or irreducible (is because of the inherently stochastic nature of the world)" (Kwisthout et al. 2017, p. 87).

a) Implications of precision for attention:

It is worth clarifying that within the framework of AI, the notion of "precise prediction" is not clearly defined but described as a process. "When I hear attention is 'taking possession by the mind in clear and vivid form,..., I think: No, it's not; attention is simply the process of optimizing precision during hierarchical inference…; attention might not be the 'selection' of sensory channels but an emergent property of 'prediction'; where high-precision prediction -errors enjoy greater gain" (Friston, 2009, p. 299).

As can be seen from this quote, it equated attention with precision, which is a crucial point within the context of MBSAT, given its mindfulness orientation. Most mindfulness interventions focus on "training attention", but with an interpretation of attention that doesn't fully appreciate its neurological function and the brain processes involved. Viewing attention as the enaction of precision within Active Inference dovetails perfectly with MBSAT's prospective orientation centered on strategic awareness.

Predictive errors travel bottom-up from superficial neurological layers towards more complex neuro layers. We increase precision by paying attention to PE signals. If the signal converges with the prediction, it validates the generative model. However, suppose the signal does not match the prediction. In that case, it continues its feed-forward trajectory along the hierarchical path gaining precision by paying more attention to the signal until it matches the generative model of the world, and the latter gets either adjusted with a perceptual update, or an action is taken to conform the prediction to the percept.

Let us consider a concrete, everyday situation. For example, I predict the cup of tea is not hot. When I touch it, and it is only lukewarm, I realize a minimal PE. If the cup is hot, showing a significant PE, the signal travels upward towards the region of the generative model, where the prediction was created, simultaneously setting in motion a calibration process, gauging the precision of the tea temperature. At one point, the model gets updated through learning, so next time I will first touch the cup of tea with

one finger to test the temperature or, if I predict the cup will be hot, I can directly take action to match the external world (the temperature of the tea) to the prediction, for example by putting a couple of ice cubes in the cup to cool it off. Please note that the action of putting the ice in the cup is also a prediction, albeit with a high level of precision, as we know that ice reduces the temperature of any drink including tea.

b) Interaction of prediction, precision and prediction errors

Remember that prediction, the precision of prediction, and prediction error are often referred to as the "three Ps" in neuroscience.

Here is an example of such a hierarchical interaction process. Imagine your boss offers you a promotion as regional manager in a tropical country with warm weather all year. Northern Europe was where you were born and raised. You simulate possible states in your mind; you know you go to warmer countries for vacation every summer, and you have always enjoyed these experiences. So, you predict you will undoubtedly enjoy the experience of living and working in such an environment. You talk to your family in the evening, and they are also excited about the offer. Your high cortical predictions are suggesting: "Yes, I will take the offer with joy." Later, you talk to a friend who has experience living in the tropical climate. He tells you spending vacation in a tropical country and living there permanently for work are two different things. He suggests you research what it is like to live in the tropics. Your friend doesn't want to influence you and therefore doesn't give you any specific advice, but strongly recommends you search for more information. Your investigation reveals concerns: long rainy seasons, tropical diseases, traffic jams, etc. These issues are now traveling bottom-up as simulations of sensory inputs of living in a tropical country, imagining, for example, sweating profusely, getting stuck in a traffic jam, perhaps even getting sick. These are sources of prediction errors you believe your family might be confronting. Now with more precision about your initial prediction that it will be fun to "enjoy the tropics," you engage in more realistic talks with your boss and negotiate: housing conditions, frequency of home travel, etc. - all resources that you and your family will require to be able to minimize Free Energy based on your current, more realistic predictions about what it is like to live in the tropics.

1.7 Summary: Our Brain's Essential Biomechanics

Let us summarize the key ideas presented so far and integrate them into a straightforward narrative that connects to the following chapters.

Our starting point was the characteristics of our postmodern society, and we noted the increasing Volatility, Uncertainty, Complexity, and Ambiguity (VUCA). There is abundant empirical evidence of distress in the world, even in advanced industrialized societies, as documented by Anne Case and Nobel laureate Angus Deaton in their book *Deaths of Despair and the Future of Capitalism* (2020). Amongst others, the authors document increased incidents of suicide out of despair in the USA. We can conclude

at prima facie that in a world dominated by these characteristics, individuals urgently need competencies to anticipate and predict socio-economic trends and impending challenges to increase their decision-making skills for lasting well-being.

With this in mind, I presented an information-theoretic quantity: Free Energy (FE). According to neuroscientist K. Friston (2006, 2010), FE is critically involved in increasing human survival prospects across different dimensions of life (biological, social, and economic) and through time. Like any biological system, life inevitably exposes humans to the effects of attrition and eventually natural decay. To keep themselves within acceptable bounds of survival opportunities, members of our society require access to the extended benefits of postmodern life such as income-generating work, housing, health insurance, and many other necessities. Hence, being sick, losing one's job, not having a house to live in, being deprived of health insurance, living in a corrupt political system and other undesirable life conditions create distress or - in the terminology of FE - states of stressful surprise. Avoiding unwanted states of surprise in our lives equals minimizing FE. When we can minimize FE, we are doing well; the models of ourselves as a flourishing individual are working.

This discovery signifies that we can have an objective function of how humans can stay alive and prosper by minimizing Free Energy. We have looked at this principle in individuals living under the necessities of life in a postmodern society. For example, losing a job and staying unemployed for an extended period reduces the chances of maintaining an acceptable existence. Yet, minimizing FE is a universal principle. Even if an individual would relinquish modern life and move, for example, to a beautiful archipelago in the Atlantic, home to the Kuna Indians for example, thus returning to a life of subsistence with no need for a job, the person would still require minimizing Free Energy out of the vital need to hunt or fish to sustain his or her livelihood.

In the subsequent sections, we have looked at the functioning of the **Bayesian Brain** (BB) and its implications for FE. Neurological findings show that the BB, instead of reacting to inputs, builds predictions about what it perceives in the environment and its internal milieu (BETA – Body sensations, Emotions, Thoughts and Action Impulses). This process resembles Bayes' statistics and consists of updating priors and their respective probabilities when new data is discovered, allowing for the formulation of posterior probability distributions. Bayesian statistics have been crucial for the development of Artificial Intelligence, including so-called machine learning based on artificial neural networks and all the data mining processes accessible in today's digitalized world. As parallels with the neurological operation of the brain became apparent, neuroscientists built the case for approximated Bayesian inferences in the brain, according to the following algorithm:

revised posterior prediction = prior prediction + (sensory signals–prior prediction) x precision

These elements form the basis for mind learning.

While researching this material, I found a certain similarity between how the brain builds predictions and a corporate finance concept. In investment theory, there is an equation for estimating expected

return: Expected return (the posterior in BB) = risk-free return (the prior in BB) + (Market return or the sensory signal–risk-free return) x a risk factor denominated as BETA (the precision in BB). I just mention this to suggest similarities between disciplines that facilitate interdisciplinary work and understanding.

Subsequently, we saw that the Bayesian Brain embodies **Generative Models** (GMs) and **Recognition Models** (RMs) of the world that are contextualized to our existential niche. They are based on our experiences and shape the circuits that generate predictions and prediction errors (Keller & Mrsic-Flogel, 2018). The parameters of the BBs are beliefs corresponding to the guesses of what we perceive with our senses (see, hear, smell, touch, or taste) and of things that loosely appear in our mind, with different values on a continuum of many possibilities or probabilities.

Then we discussed that BB models are implemented through a process of **Active Inference** (AI) composed of three elements: prediction, prediction errors and precision, the three Ps, and that it is the proper conjugation of these elements that allows minimizing FE, where minimizing Free Energy corresponds to minimizing predictive errors which can only be done in two ways: either by changing the prediction via new information or by changing the world that is by acting in the world. In brief, BB is modeled from continuous variables of recognition of events and previous subjective experiences of the observer and based on the likelihood of the observations given the earlier adventures of the person and new information.

The conceptual trio composed of the Free Energy Principle, the Bayesian Hierarchical Brain, and the Active Inference mechanism with its three computational quantities: predictions, prediction errors, and precision represent a robust theoretical framework for training strategic awareness and skillful decision making. It supports a scientifically grounded, powerful, and practical approach that can guide people in their search for a flourishing life. Precisely when we are confronted with the challenges of our VUCA world, we can continually update our Generative Models and refine our Recognition Models using Active Inference to mind our internal and external world.

Finally, these theories are a tightly researched line of reasoning about the mechanisms of the brain and its influence on the life of individuals. The ideas conform to Marr's three levels of analysis (Marr, 1982, p. 24-27):

1) computational:
   optimizing Free Energy/minimization of prediction errors

2) algorithmic:
   the process of Active Inference and

3) implementation:
   continuous implementation of the 3 Ps: enaction of Prediction, Prediction Errors, and Precision.

Also, at a practical level, the theories stand for a regulatory mechanism that skillfully guides the interface between people and their environment. "Every good regulator of a system must be a model of that

system… the living Brain, so far as it is to be a successful and efficient regulator for survival, must proceed, in learning, by the formation of a model (or models) of its environment… Now that we know that any regulator must model what it regulates, we can measure how efficiently the brain carries out this process. There can no longer be a question about whether the brain models its environment: it must." (Conant & Ross Ashby, 1970, p. 82)

These insights confirm the potential for strategic awareness training. They show that awareness training to update our brain models is necessary for productive functioning and living in our existential niche.