EYŞAN DEMIRKAYA PATHOLOGICALLY CHRONIC PAIN AND PAIN AVOIDANCE BEHAVIOR WITHIN THE PREDICTIVE PROCESSING FRAMEWORK Bilkent University 2021

PATHOLOGICALLY CHRONIC PAIN AND PAIN AVOIDANCE BEHAVIOR WITHIN THE PREDICTIVE PROCESSING FRAMEWORK

A Master's Thesis

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To Ayşe, Abdil, and Jack

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ABSTRACT

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Pain as the most enquired philosophical theme is a complex experience, which includes sensation, emotion, motivation, cognition, and social interaction. However, there is not a single overarching philosophical theory that accounts for all the dimensions of pain. The most overlooked discussion of pain is on its motivational aspect; yet, it is indispensable for an integrated understanding of pain. Also, its least debated area is the substantial relation between pathologically chronic pain and action. In this thesis, I attempt to investigate why physiologically acute pain outlasts its purposes to transform into pathologically chronic pain and why pathologically chronic pain is accompanied by pain avoidance behavior by drawing inferences from the explore-exploit dilemma. I also examine the related pain theories addressing their

failures in answering these questions. I conclude that analyzing pathologically chronic pain and pain avoidance behavior within predictive processing framework (1) provides an active learning account for pathologically chronic pain, (2) ensures an active inference account for pain avoidance behavior, (3) allows an active learning account for pain avoidance behavior only if certain conditions are met, and (4) points out the disparate action strategies are accountable for pathologically acute pain, pain avoidance behavior, and physiologically acute pain.

Keywords: Active Inference, Active Learning, Explore-Exploit Dilemma, Pain Avoidance Behavior, Pathologically Chronic Pain

ÖZET

ÖNGÖRÜYE DAYALI İŞLEME ÇERÇEVESİ İÇİNDE PATOLOJİK KRONİK AĞRI VE AĞRIDAN KAÇINMA DAVRANIŞI

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Yüksek Lisans, Felsefe Bölümü

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Ağrı, en çok araştırılan felsefik temalardan biri olarak, algı, duygu, motivasyon, biliş ve sosyal etkileşimleri içeren kompleks bir deneyimdir. Fakat ağrının tüm boyutlarını kapsayan bir felsefe teorisi bulunmamaktadır. Ağrı tartışmalarında en çok gözardı edilen ağrının motivasyon boyutudur; bununla birlikte motivasyon, ağrının bütüncül bir anlayışı için temel bir bileşendir. Ayrıca, ağrının motivasyon yönünün en az tartışılan alanı patolojik kronik ağrı ile eylem arasındaki önemli ilişkidir. Bu tezin esas amacı fizyolojik akut ağrının fonksiyonlarını kaybederek neden patolojik kronik

ağrıya dönüştüğüne ve ağrıdan kaçınma davranışının patolojik kronik ağrıya neden eşlik ettiğine keşfet-faydalan ikileminden çıkarımlarda bulunarak cevap aramaktır. Bu tez aynı zamanda ilgili ağrı teorilerini ve onların bu soruları cevaplamadaki başarısızlıklarını inceleyecektir. Bu tezden çıkarılan sonuçlara göre, öngörüye dayalı işleme çerçevesi (1) patolojik kronik ağrıyı aktif öğrenme ile açıklar, (2) ağrıdan kaçınma davranışını aktif çıkarım ile izah eder, (3) ağrıdan kaçınma davranışını yalnızca belirli koşullar sağlandığında aktif öğrenme ile ifade eder ve (4) farklı eylem stratejilerinin patolojik kronik ağrıdan, ağrıdan kaçınma davranışından ve fizyolojik akut ağrıdan sorumlu olduğuna işaret eder.

Anahtar Kelimeler: Ağrıdan Kaçınma Davranışı, Aktif Çıkarım, Aktif Öğrenme, Keşfet-Faydalan İkilemi, Patolojik Kronik Ağrı

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INTRODUCTION

How can an inactive blueprint of the human brain that gives rise to an active agent be achieved? One approach to this question is to scan the brain, which, falls into the scope of neuroscience. Scanning is a way of producing the detailed images of the human brain by the magnetic fields and radio waves (MRI and fMRI) or X-rays (CT) or electrical charges (EEG) (Glover, 2011). Yet, these scanning techniques are not nearly good enough to capture all the activities in the human brain. There are two reasons for this situation. Initially, there are technical challenges in scanning such as noise signals, image distortions, and signal dropouts. Secondly, the human brain is complex. There are approximately 100 billion neurons in the human brain while these are in communication with one another through one million billion synapses ("Brain Facts and Figures", 2021). Signals are fired reaching to one thousand times every second. This implies that up to one quadrillion signaling events occur each second. What's more, there is a lot more to the human brain than the neuronal cells and signals. There are 10- to 50-fold more non-neuronal cells including the glial cells, immune cells, neurotransmitters, neuromodulators, and hormones (Herculano-Houzel, 2012: 1). Some glial cells such as astrocytes, microglia, and oligodendrocytes have a role in memory formation (Hertz & Chen, 2016: 1). To give an example, GABA neurotransmitters are responsible for pain relief (Yowtak, Wang, Kim, Lu, Chung, & Chung, 2013: 2469). The impact of immune T cells on stress responsiveness

exemplifies immune cells' implications to the human brain functions (Morimoto & Nakajima, 2019: 1). For instance, the neuromodulator histamine has a vital function in learning (Tasaka, 1994: 27). Also, androgen is linked with visuospatial ability (Ali, Begum, & Reza, 2018: 34). Further, the human brain is influenced by the other bodily parts such as heart nerves and gut microbiome. For example, heart nerves affect attention and motivation (McCraty, Atkinson, Tomasino, & Bradley, 2009:16). Another example, a type of bacteria called Lactobacillus within the human gut microbiome increases the appetite for sugar (Leitão-Gonçalves, Carvalho-Santos, Fioreze, Anjos, & Baltazar,, 2017: 1; Appleton, 2018: 28). Through the efforts of researchers from various disciplines encapsulating the microbiologists, geneticists, biochemical engineers, chemists, medical doctors, and psychologists, a basic understanding of their functions at small scales is already known but an understanding of their functions at larger scales is still elusive.

A new promising neuroscientific method, which is cutting the brain into a number of small slices and then scanning them with a high resolution electron microscope is used recently (Zhu, Cizeron, Qiu, Benavides-Piccione, Skene, Fransèn, Komiyama,& Grant, 2018). The novelty of this approach comes from its surpassing challenges in scanning. In particular, a cubic millimeter of the mouse brain containing a hundred thousand neurons with a billion connections was cut into 25 thousand slices (Zhu et al., 2018: 781). Five electron microscopes scanned them for five months collecting more than 100 million images. Additionally, the formation of a 3D model out of 100 million images of a single cubic millimeter of the mouse brain took three months.

Further, the data gathered from it took up 2 million gigabytes of cloud storage. To scan the human brain, this whole endeavor has to be replicated a million times, since the human brain has around one million billion synapses. Consequently, complete data of the human brain would take thousands of years and two million petabytes. Surprisingly, these are just for mapping synapses. For a complete scanning of the human brain, each influencer of the human brain must be mapped out. More importantly, this would take millions of years and more data storage than that on the Earth. On top of that, all this effort provides a static mapping of the human brain instead of an active wiring of an agent. In order to reach an understanding of an active agent, the laws and rules governing the activity of the human brain at micro- and macro-level are necessary.

As opposed to these neuroscientific approaches, there is a propitious computational approach called the predictive processing. Particularly, it suggests that it might not be necessary to scan everything in he human brain and its influencers. The human brain can be simplified into the probabilistic internal generative models that could match the human brain regarding its functions. To exemplify, a probabilistic generative model of the human brain can learn or false learn, remember or forget, imagine or dream, develop an action or remain inactive, and so forth. By simplifying the human brain into the generative models, it can be attained how the static mapping of the human brain leads to an active agent (Friston, 2010; Clark, 2013; Hohwy, 2013). However, similar to the human brain's development of myriad disorders, a generative model can develop a number of maladies. Specifically, if a probabilistic generative

model of the human brain is damaged in any of innumerable ways, then the agent may be in persistent pains, intermittent hallucinations, or endless delusions.

From the faculties of the human brain to its disorders, maybe, the most peculiar thing about the human brain is pain. There are three reasons for that: (i) it is not a process that can be explained fully biochemically because the human brain's pain answer is distributed across multiple brain areas (Corns, 2015: 3), (ii) it is not a proper scientific subject because it is indicated only by subjective report (Corns, 2018:1), (iii) the success rate of pain targeted treatments is not 100% implying that patients who suffered from pain will continue to suffer, and that pain management overrules pain treatment in the medical arena (Main, Spanswick & Bartys, 2000).

Yet, the computational approach to the human brain may promise innovative advancements particularly in understanding the emergences, maintenances, and treatment of experiences such as pain. Thus, in this thesis I investigate pathologically chronic pain and pain avoidance behavior within the predictive processing framework. Specifically, I ask why physiologically acute pain outlives its purposes to become pathologically chronic pain, and why pathologically chronic pain is accompanied by pain avoidance behavior. I argue that by casting physiologically acute pain, pathologically chronic pain, and pain avoidance behavior as Bayesian probabilistic inference problems, different mechanisms having roles in the development, continuation, and treatment of distinct pains and behaviors emerged.

These mechanisms encapsulate perceptual inference, active inference, and active learning.

I aim (i) to expand the predictive processing framework to pathologically chronic pain and pain avoidance behavior associated with the persistent pain by examining the explore-exploit dilemma, (ii) to make it mechanistically-explicable, (iii) to render it scientifically objectively comprehensible, and (iv) to pave the way for its treatment. In Chapter 1, I start by reviewing the pain theories that come to the front in the Philosophy of Mind, which are composed of evaluativism, imperativism, psycho-functionalism. I then discuss some of the worries that gained prominence in the literature. I also discuss whether or not these theories could tackle the main questions of the thesis.

Chapter 2 shifts the conversation on pain to the review of the predictive processing framework. In this chapter, I discuss the conceptual background of the framework. That is, I demonstrate how this framework roots from Bayesian Brain Hypothesis and the Predictive Coding Theory. I conclude the chapter by overviewing perceptual inference, active inference, and active learning.

Throughout Chapter 3, I examine why physiologically acute pain outstays its functions to turn into pathologically chronic pain, and why pathologically chronic pain is associated by pain avoidance behavior. I claim that the main reason that distinct mechanisms take part in gaining information and producing actions regarding

physiological acute pain, pathologically chronic pain, and pain avoidance behavior is because of the influence of discrete levels of uncertainty on them. Through the explore-exploit dilemma, I draw the observation that active inference and active learning lead to the emergence and the preservation of pain avoidance behavior and pathologically chronic pain, respectively. I also demonstrate how the perceptual inference explains the sensory and perceptual character of both physiologically acute pain and pathologically chronic pain. Before I conclude, I revolve around the implementations of the thesis in the scope of philosophy, neuroscience, and psychiatry.

CHAPTER I

PAIN

What is taken for granted regarding pain is that it is a complex, convergent, and multidimensional experience (Krahe, Springer, Weinman, & Fotopoulou, 2013). It encapsulates sensation, emotion, motivation, cognition, and social interaction. That is, it is modulated by bodily sensations (i.e., nociception), affect (i.e., attitude), evaluation (i.e., appraisal), action (i.e., volitional or involuntary behavior), and cognitive processes (e.g., attention, expectancy, or mood) and interpersonal interactions. It has phenomenal character, like other experiences with bodily sensational component, such as hunger, tickles, and itches. Its affective character is, mostly, unpleasant although there are cases of pleasant pain as well. When it is unpleasant, it motivates the body to take an action to mitigate it. If it is pleasant, then an action is taken by the body to protract it.

Yet, little is known about the nature of pain and its biological markers in the human brain (Corns, 2016: 2950; Corns, 2018: 1). In the first instance, pain may be

physiological, pathological, or *nociplastic* (Woolf, 2010: 3742). Physiological pain is crucial for physiological, adaptive and *protective* system of the body. It detects the noxious incoming data and tissue damage, and signals for maintaining the integrity of the body. In the former case, this kind of pain is also called *nociceptive pain* because it relies on nociception (Figure 1A). Yet, if it is the latter, then it is also named *inflammatory pain* because it originates from inflammation on tissues due to damaging (Figure 1B). The adaptive and protective function of physiological pain calls for *action* such as relatively simpler behavior like withdrawal reflex or relatively more complex behavior like avoidance behavior. Consider an infant's encounter with the burn of the fire of a candle, the cut of the sharp edge of a knife, or the ice burn of the coldness of an ice cube. After the very first experience of the infant with the hot, sharp or cold objects, a withdrawal reflex may be demanded, whereas the following experiences may demand an avoidance behavior. Alternatively, an inflammation on the body as in the case of rheumatoid arthritis may call for an avoidance behavior. However, pathological pain is *not protective*, and it is *maladaptive* (Woolf, 2010: 3742). It is *dysfunctional*. It stems form malfunctioning of the nervous system because of a disease or a disorder damaging or irritating the nervous system. It is also mentioned as *neuropathic pain* (Figure 1C). In addition, *nociplastic pain* is *not protective* (Woolf, 2010: 3742). It is *maladaptive* and *dysfunctional,* as well (Figure 1D). Unlike pathological pain, it does not derive from a disease or a disorder. Consider a nociplastic pain due to fibromyalgia.

Additionally, a physiological pain may be *acute* or *chronic* (Figure 2A and 2B). If it is acute, then it is *short-lived*—i.e., lasts less than six months, while if it is chronic, it *persists*—i.e., lasts more than six months (Grichnik & Ferrante, 1991:217). Further, acute pain is treatable, whereas chronic pain is irrespective of a current disease or disorder. Consider *physiological acute* tissue trauma pain resulted from stepping on a lego piece. Alternatively, consider *physiologically chronic pain* sprung from osteoarthritis. However, pathological pain may be acute or chronic. Consider *pathological chronic pain* brought about by stroke, spinal cord injury, multiple sclerosis, amputation, or diabetes. What's more, whether a pain is physiological, pathological, or nociplastic, what its matrices, biological processes, or neurological activation patterns are difficult to track down because when such neuroscientific methods are used, multiple areas of the human brain light up (Garcia-Larrea & Peyron, 2013: S30). That is, brain is *not modular* when it comes to pain.

Apart from the nature of pain and its biological markers in the human brain, from whether or not pain is a natural kind to whether it is a mental experience, a bodily condition, or a representation, the controversies are numerous (Corns, 2018: 14). Further, if it is a representation, then the kind of representation is controversial. The neuroscientific approaches and the computational approach to the human brain, which aim to explain how an inactive wiring of the human brain generates an active agent, share an assumption. It is called *strong representationalism* according to which *all* mental states and processes are *representational* (Armstrong, 1961). In detail, it argues that a mental state is *exclusively* determined by its *intentional content* (Dretske,

1995; Tye, 1995). In parallel, a representation is a mental object that bears an informative intentional content. For example, physiologically acute pain represents a physiological disturbance.

Strong representationalism grounds these approaches to the human mind and has an advantage over its weaker version holding that the intentional content does not ground the mental state (Block, 1990) because it can explain all mental states and processes with qualitative character by reducing the phenomenal character to the intentional content. A qualitative character refers to "what it is like for one to be in that mental state" (Block, 1990). The bodily sensations such as hunger, tickles, itches, and pain have qualitative character. They pose a challenge for the weaker version of the representationalism. Particularly, what it is like to be in a physiologically acute pain experience for an agent cannot be accounted by the weak version of representationalism.

However, the strong version of representationalism is not free of challenges. The opponents of the strong representationalism attack to pain's affective and motivational characters. Initially, all mental states and processes with affective character present a challenge for the strong version of representationalism. For instance, pain is affective in its nature. It is felt as either pleasant or unpleasant. That is, pain involves an attitude. Yet, the stronger version of representationalism cannot account for the affective character of pain. Additionally, pain motivates an agent to take an action. Yet, this motivational character of pain is not accounted by the strong

version of the representationalism. To explain the phenomenal, sensory, affective, and motivational characters of pain, *evaluativism, imperativism,* and *psycho-functionalism* emerge.

1.1 Evaluativism Regarding Pain

The *evaluative perceptualist* theory regarding pain argues that pain is a *perception.* That is, pain has a modality-specific character called *sensory character*. This sensory character refers to the bodily condition. Evaluativism is, also, an *intentionalist representationalist* theory, which claims that pain *represents* a sort of bodily disturbance. This object of perception has an *intentional content*. It *indicates* that "*something that is sensory*—i.e., a kind of physiological disturbance, *is the case"*. In this regard, it is an *indicative content*. In parallel, it needs to satisfy an *accuracy condition*. That is, it either affirms or denies that something is the case.

Aside from its sensory character, evaluativism holds that unpleasantness or pleasantness of pain—i.e., *its affective character*, forms *evaluative content* of the representation (Bain, 2013). Consequently, according to evaluativists, there is a single representation composed of two distinct contents, which are called *indicative content* and *affective content.* Suppose that one drinks a glass of sour milk, and that therefore, she feels a specific type of pain in her stomach. Her pain represents that (i) a physiological disturbance in her stomach is the case, and (ii) this particular disturbance is unpleasant for her.

However, there are, mainly, three worries about evaluativism regarding pain. First, *the messenger-shooting objection* comes against the perceptualist aspect of evaluativism (Jacobson, 2013). Particularly, how evaluativism, like any perceptualist theory, explains the motivational character of pain appears to be problematic. It suggests that pain as a representation is equivalent to a messenger that informs the perceiver about the bodily disturbance. Given that pain's motivational character is what drives the perceiver to eliminate that pain when it is unpleasant for the perceiver, representing the physiological disturbance that motivates to get rid of the pain is equal to shooting the messenger. Yet, it is not clear that how shooting the messenger eliminates the bodily disturbance. For example, one receives an e-mail from her downstairs neighbor informing about the leakage from her ceiling that is unpleasant for her downstairs neighbor and her. In this setting, the e-mail functions as a representation with an informative indicative content and an affective content. Nevertheless, this e-mail does not give her a motivation to fix the leakage coming from her apartment. Additionally, deleting the e-mail does not mean that the leakage is fixed. Analogously, pain perception does not motivate its perceiver to eliminate the bodily disturbance.

The second objection attacks evaluativism's representationalist aspect. It is called *the problem of semantic focus* (Aydede, 2009). Specifically, whether the semantic focus is on pain itself or on the semantic concepts that are related with the bodily disturbance is problematic. It proposes that when a bodily disturbance is perceived by a perceiver, the semantic concept PAIN is not applied to the bodily disturbance. The

semantic focus is already on the pain experience itself. For instance, in a scenario, in which one perceives a traffic light, vision is the modality, and the color information is the information that is specific to the visual modality. The object of this perception is the traffic light. At the same time, this perception leads to the attachment of the semantic concepts such as RED, YELLOW, or GREEN, which become parts of the object of the perception.

The last objection attacks evaluativism's intentionalist aspect. It is concerned with the accuracy condition of the representation's indicative content. That is, the necessary conditions that make the bodily disturbance an unpleasant pain accurate or inaccurate are still unclear (Corns, 2018: 6). Particularly, in evaluativism, a representation *indicates* that something is the case. In this respect, it has an indicative content that contains an accuracy condition. In other words, whether something is the case or not implies the accuracy condition of the representation. If a pain is a representation that *accurately represents* that the bodily disturbance is the case, then it is *misrepresentation* that *inaccurately represents* that the bodily disturbance is the case. It is possible that pain is a misrepresentation as well as that it is a representation. That is, whether all pains are misrepresentations or some pains are representation is not explicit in evaluativism. In the case of phantom pains of amputees, for example, a pain felt on an amputated limb is an inaccurate representation of a bodily disturbance. Hence, the phantom pain exemplifies a pain that is a misrepresentation. Yet, a pain felt on a healthy limb of the amputee due to accidentally hitting it on a wall may exemplify a pain as an accurate representation of the bodily disturbance.

In connection with the first and the third objections, I have an additional worry. If evaluativism is true, then how physiologically acute pain turns into pathologically chronic pain is problematic. In detail, pain is an overarching term that involves mainly physiologically acute pain and pathologically chronic pain. Pain caused by a broken leg bone is an example of a physiologically acute pain, while a neuropathic pain is an instance of pathologically chronic pain. Both are felt in certain areas of the human body with varying degrees of intensity. The acute and chronic pain perception differs from each other with respect to their motivating force for an action and their accuracies regarding their felt places and intensities. In an evaluativist setting, they appear to be problematic in some ways. First, if evaluativism is true, then physiologically acute pain is purposeful—i.e., it has a sort of utility for the perceiver such as warning the human body from of injury and motivating her to take an action. Second, if evaluativism is true, then physiologically acute pain is an accurate representation of either internally- or externally-caused sensation of the bodily disturbance. At the same time, if evaluativism is true, then pathologically chronic pain is, also, purposeful. Supplementally, if evaluativism is true, then pathologically chronic pain is an accurate representation because it accurately represents a sensation of the bodily disturbance. However, it is not the case that pathologically chronic pain is purposeful and an accurate representation of a bodily disturbance. Therefore, evaluativism does not account for what results in a misrepresentation that was once a representation and the lack of motivation for an action-taking that was once there.

1.2 Imperativism Regarding Pain

The imperative representational theory of pain holds that pain *represents an imperative*. This representation—i.e., the command, has an *intentional content*. In parallel, this intentional content forms the command's *imperative content*. Different from evaluativism, it represents that "*something is to be done"* in imperativism (Klein, 2015). In this respect, it comprises information about an action performed by the agent. The action may be either to stop doing something or to protect the human body. Additionally, as opposed to the accuracy condition of the indicative content in evaluativism, the imperative content has a *satisfaction condition*. That is, it either satisfies or dissatisfies that something is to be done. In parallel, pain motivates doing or acting on something directly through its imperative content (Hall, 2008: 530). However, some pains may represent an *unsatisfiable* or *an already satisfied command.* Consider headaches, neuropathic pains, and phantom pains as examples to such pains (Martinez, 2015).

There are mainly three arguments against imperativism with regard to pain. The first argument against imperativism with regard to pain is concerned with the imperative content of pain. In particular, it argues that there are some pains that do not motivate their agents to take actions, and they are problematic for imperativism. Consider that morphine pain and pain after lobotomy do not result in action (Grahek, 2007). The second argument against imperativism is about the pain's imperative content, which is called *the problem of authority* (Bain, 2011: 180). Precisely, it contends that a command does not motivate an agent to execute an action concerning pain, and there

is a problem of authority in imperativism. What motivates a system or an agent to take an action is the *reason*, which gives the authority to the system or the agent herself. The third argument against imperativism concerning pain is about the sensory and affective characters of pain (Corns, 2018: 9). Clearly, it asserts that imperativism concerning pain does not account the pain's sensory and affective characters, although it reflects the motivational aspect of pain.

In addition to these three worries about imperativism regarding pain, I have an additional worry. How physiologically acute pain turns into pathologically chronic pain is problematic for imperativism similar to that it is the case for evaluativism. To be specific, what changes the satisfaction command of an acute pain to the satisfaction command of a chronic pain is unclear in imperativism. That is, what determines the move from being satisfiable to being unsatisfiable is elusive. In other words, the condition for an unsatisfiable pain is lacking in imperativism. For instance, if evaluativism is true, then a phantom pain necessarily remains unsatisfiable. However, this is not the case in that Ramachandran's mirror-box approach to phantom pain satisfies such pains (Ramachandran, 1998).

1.3 Psycho-functionalism Regarding Pain

Contrary to evaluativism and imperativism, psycho-functionalism is a theory against the strong representationalism. It holds that pain *represents* a kind of bodily disturbance as its *sensory intentional indicative content*. Unlike the evaluativists and the imperativists, however, the psycho-functionalists reject the argument that the

affective character of pain has an *intentional indicative content* because because it has a qualitative character and a functional character irrespective of the accuracy condition of a representation's content. That is, regardless of whether there is a representation or misrepresentation, it functions in the development of the affective-motivational character of pain.

Instead, the affective and motivational characters of pain arise from *the processing* of the representation's indicative content. This is called *m-processing* occurring at sub-personal level. The m-processing of a sensory information leads to either *attraction* or *aversion.* This forms *phen-desiring*, which refers to the formation of desires regarding either pleasant or unpleasant content. In addition, m-processing results in *phen-beliving*. That is, it has a role in the formation of beliefs concerning the sensory information. Further, m-processing which is composed of phen-desiring and phen-beliving shapes *reason for action*. If there weren't a reason for an action, then a command would not motivate an agent to take an action. Also, if there is a reason for an action, there is no need for a command. Therefore, m-processing gives rise to actions, desires, and beliefs without an affective intentional content, as in evaluativism, and without a command, as in imperativism.

Against psycho-functionalism, there is one major worry. It is about its sub-personal aspect. To be specific, it argues that sub-personal level m-processing does not elucidate the normative reasons for action (Bain, 2013). In order to explain the normative motivations to act, personal level processing is necessary. Additionally, I

have a further worry about psycho-functionalism. Similar to the case for both evaluativism and imperativism, the way, in which a physiologically acute pain becomes a pathologically chronic pain, creates a problem for psycho-functionalism. Namely, if psycho-functionalism is true, then all agents with pathologically chronic pains must have the same sub-personal and functional processing. Otherwise, an agent with a slight individual difference in the sub-personal and functional processing does not count as having pathologically chronic pain. It is, yet, the case that pathologically chronic pain manifests individual differences from one agent to another although these individual differences are not accounted scientifically at the sub-personal level. Therefore, psycho-functionalism cannot explain the individual differences of the agents with pathologically chronic pain.

CHAPTER II

THE PREDICTIVE PROCESSING FRAMEWORK

From the conversation on pain, I move the dialogue toward the conceptual background of the predictive processing framework before examining pathologically chronic pain and pain avoidance behavior. Particularly, this framework roots from Bayesian Brain Hypothesis and the predictive coding theory. Nevertheless, the fame of the predictive processing framework comes from perceptual inference, active inference, and active learning. Thus, I start by providing an overview of Bayesian Brain Hypothesis and the predictive coding theory. Then, I dwell into perceptual inference, active inference, and active learning before inquiring why physiologically acute pain outlives its protective and adaptive functions to turn into pathologically chronic pain and why pain avoidance behavior and pathologically chronic pain are associated.

2.1 Bayesian Brain Hypothesis

One of the approaches to cognition is Bayesian Brain Hypothesis. It is an overarching hypothesis composed of several different models to account for divergent domains

and distinct levels of cognition. Importantly, it is the underlying hypothesis of the predictive processing framework. The main tenet of this hypothesis is that brain is a *Bayesian inference machine* (Friston, 2010). The underlying principle of this view is that the brain has only *indirect access* to the bodily internal states and the environmental external states. Consequently, it must *infer* the sources or causes of these states. That is, brain *generates probabilistic internal inferences* following *Bayes' rule*.

Then, what is a Bayesian probabilistic inference? A *Bayesian inference, prediction, belief* or *information* is a *statistical probability distribution over an unknown source or cause of a state* (Friston, 2010). In that sense, Bayesian beliefs are different than the explicit propositional beliefs.

Particularly, *Bayes' rule* or *Bayes' theorem* is a means of computing a probability of predictive information when other certain probabilities of predictive information are known. Its formula is as follows.

$$P(A|B) = P(A)\, P(B|A) / P(B)$$

This formula tells us that suppose there are two separate predictive information call 'A' and 'B'. What we want to find is P(A|B) when P(A), P(B), and P(B|A) are known. P(A|B) tells us how often 'A' happens given that 'B' happens. P(A) tells us how likely 'A' is on its own. P(B) tells us how likely 'B' is on its own, and P(B|A) tells us

how often ‘B’ happens given that ‘A’ happens. In other words, P(A|B), which is a probabilistic inference reflects the integration of P(A), P(B), and P(B|A), which are predictive information, in an approximately Bayesian optimal way.

What can be the sources or the causes of predictive information? Namely, the sources of these predictive information can be either *the prior predictions— the priors,* that are encoded in the generative model or *the likelihoods* of the current potentially multi-sensory noisy information. If a belief is *prior to an observation* of a sensory input, then it is called a *prior belief*. Additionally, the likelihood is the *sensory evidence* (Figure 3).

What does the Bayesian optimal integration mean? It is an *optimal integration* because it is based on their *precision* or *uncertainty weights* (Figure 3). That is, the predictive information that has more precision influences the integration more. In parallel, the more uncertain predictive information is, the less the influence is on integration (Figure 4). Nevertheless, optimality does not refer to accuracy (Tabor & Burr, 2019: 58). Thus, there may be a decoupling between a likelihood about incoming sensory information and a prior. Therefore, Bayesian optimal integration can result in a detachment from veridical sensory evidence.

What is got after the Bayesian optimal integration, then? If a prior belief is Bayesian optimally integrated to either another prior belief or likelihood after observation of a new sensory data, then a new belief called a *posterior belief* is formed (Figure 4). Yet,

it is essential to note here what governs the Bayesian optimal integration. That is, the likelihood and the prior do not necessarily match. The *mismatch* between them governs the posterior formation through the Bayesian optimal integration. In other words, the Bayesian optimal integration is centered on the comparison and adjustment of the prior belief and the sensory input.

However, why is the Bayesian optimal integration necessary, and why is it maintained over time? It is required for the formation of a belief that will be necessitated for the access to the source of a state. It is maintained in order to increase the degree of precision that is associated with a belief. That is, a belief is attached with a certain degree of *precision*. In other words, precision implies *certainty* that is associated with a belief. The precision of a belief, which is based on a sensory input, is tested against the precision of the sensory data. Further, the precision of the sensation provides either *evidence in favor of* or *evidence against* the prior belief.

What is the evidence against a prior belief in light of sensory data? It is *the precision of prediction error*, which is calculated via the difference between the precision of the sensory data and the precision of the prior (Figure 3). That is, the precision of the prediction error provides how much evidence is given. In this respect, what governs the Bayesian optimal integration is the *prediction error.*

Does this imply that the Bayesian optimal integration is biased?. Based on the relative precision of the sensory input and that of the prior—i.e, based on the precision of the

prediction error, the posterior belief biases toward either of them. Suppose that the posterior belief is biased towards sensory evidence by either increasing the precision of sensory input and/or failing to attenuate it or decreasing the precision of the prior belief (Figure 4-5).

What is exactly the function of the prediction error? It is signaling *learning*, which occurs through the Bayesian optimal integration. How much learning is occurred is called *the learning rate*. It is calculated by the ratio of the precision of the prediction error and the precision of the prior. Consider that the prior is constant, the learning rate relies on the precision of the sensory input. In this sense, the learning is open to change and the learning rate is variable. In parallel, a system can adapt to dynamically altering uncertain environment.

However, how can the learning rate be increased allowing a system to adapt to its environment? It is ensured though a single imperative, which is *the minimization of prediction error.* It is important to note that, the prediction error minimization should occur *over the long-term average*. To exemplify, if the precision of prediction error is too large, then the prediction error minimization will be excessive and the learning rate will be vast. Through prediction error minimization, a system adapts to its ever-changing and uncertain environment.

What, more importantly, can a prediction error signal other than learning? It is *false learning.* That is, the predictive error minimization leads to *maladaptation* to an

environment. False learning or maladaptation to an environment is probable. If the precision of the sensory input is *overestimated* or the precision of the prior is *underestimated*, then the precision of the prediction error will be huge. This situation yields that the posterior moves towards the sensory mean and away from prior mean. Consequently, this results in *false belief* or *false inference*. This culminates in a maladaptation of the system or the agent to the body or the environment.

2.2 The Predictive Coding Theory

The predictive coding or *Bayesian coding hypothesis* is the first steps of the predictive processing framework. It depicts that beliefs are encoded in the form of probabilitydensity distributions (Friston, 2010; Clark, 2013). Having said that probability density distributions encode uncertainty, encoding beliefs implies that the neural systems of biologically possible models take uncertainty into account fundamentally. Therefore, this hypothesis postulates that brain's learning can be cast in terms of statistics, in which uncertainty is transmitted within the neural networks (Rao & Ballard, 1999: 79). It suggests that, through this way, the neural networks optimize their connectivity and the dynamics among them in order to maximize the evidence for its generative model of the environment (Hohwy, 2016: 259).

2.3 The Predictive Processing Framework

The predictive processing framework casts Bayesian probabilistic inference pertaining to *the prediction error minimization* over the long-term average (Hohwy, 2013; Clark, 2013). That is, an internal generative model of a system or an agent

produces innumerable beliefs that are directed to capture the incoming sensory information. Then, what is a generative model? A hierarchical probabilistic internal generative model is used to generate an expected consequence that may arise from hidden (latent) state of the body or the environment, and, even, in the absence of the external stimulation (Figure 6). It is shaped over time to reflect a precise representation of the body and the environment. The prior beliefs are formed by the relatively higher mental states and carry weight with the relatively lower mental states, and that therefore, they are called *top-down beliefs* (Tabor & Burr, 2019: 55). The sensory data is created by the relatively lower mental states and carry weight with the relatively higher mental states. In parallel, they are also named *bottom-up beliefs* (Tabor & Burr, 2019: 55). In this regard, there is a hierarchy of beliefs within the model of the system. There are also *bidirectional* connections among them. That is, there are *multi-level* connections among beliefs. The internal generative model chooses the top-down belief that best matches with the sensory input thereby the prediction error between the prior belief and the sensory data is minimized. After the countless trials of matching of the priors with the inputs, the internal generative model of the system promises the prediction error minimization *over the long-term average.*

The reason lurking behind the process of prediction error minimization over the long-term average within the predictive processing framework is the hierarchical internal generative model's encoding of the probability distributions of the beliefs with *uncertainty*. The uncertainty encoded in the generative model is tackled with the *precision-weighting process*, where a belief associated with the highest precision is

weighted against the others. By the transmission of the difference between the belief with the highest precision and the actual sensory input in the form of *prediction error*, the prediction error minimization occurs. The repetition of this process results in the prediction error minimization over the long-term average, in which the prediction error gets closer and closer to zero and the match gets closer and closer to exact match.

2.3.1 Perceptual Inference

Perception is a process of probabilistic knowledge-driven inference in the predictive processing framework (Clark, 2013: 2). It arises as a result of the successful prediction-error minimization. To infer the source or the cause of an incoming sensory information or *to perceive* is *perceptual inference* (Clark, 2013: 6; Hohwy, 2013: 14). It refers to a mechanism that aims to meet the encoded sensory data with a prior belief of the hierarchical internal generative model of a system or an agent. That is, the prior is tested against the actual sensory input.

An internal generative model encodes beliefs about the body and the environment as multiple top-down probability distributions with differing degrees of uncertainty. These reflect a range of candidate beliefs about the potential causes of the sensory state of the body or the world. Therefore, the prior belief of the generative model may be from various spatial and temporal levels.

However, it is *not exact* issue of matching the prior directly with the sensory input. It is directed to minimize the prediction error that arises from the difference between the sensory information and the prior over the long-term average (Clark, 2013: 7). Given that, it aims to use the prediction error as a *learning signal* to revise the system's internal generative model of its body and environment, the perceptual prior beliefs refer to what the generative model has learned from its previous encounters with the source of the incoming sensory data (Clark, 2013: 7). When the prior beliefs are tested against the actual incoming sensory information, the evidence for the internal generative model is maximized for the accurate and precise beliefs. Further, the process of matching the prior with the sensory input involves computing various probability distributions of the sensory data (Clark, 2013: 7). The reason is that an inference may be consistent with many distinct sets of causes. They can be distinguished only by *their relative probabilities of occurrence*.

2.3.2 Active Inference

Action, within the predictive processing framework, is an inferential process (Clark, 2013: 6). The inference of an action by a system or an agent results in either an inferred *outcome* or predicted *information* through the action. In this regard, the inferred action is either *exploratory* or *exploitative*. That is, the system selects either an exploratory or exploitative optimal action policy to achieve what is estimated. The policy means a sequence of states leading to the concrete action or behavior. Under the selected policy, prediction errors may be induced because of the mismatch between what is estimated and what is the current case. The system selectively

samples inputs to minimize the prediction errors under that action policy. To selectively sample, the system may alter its actions under that policy, thereby the sampled input may better reflect the predicted outcome or information.

In parallel, there are two kinds of mechanisms described under active inference (Friston, FitzGerald, Rigoli, Schwartenbeck, O'Doherty, & Pezzulo, 2016: 864; Gadsby & Hohwy, 2019: 3). A particular mechanism of active inference is for *utility*. It is for reaping an outcome or reward. The other mechanism of active inference is for *epistemic value*. It is for reducing uncertainty about a system's internal generative model of its body or environment. Importantly, under active inference process, the systems cover the reduction of uncertainty within its model by means of fixing the model and changing its actions.

2.3.3 Active Learning

An active system or agent minimizes prediction errors through either by carrying out actions to sample input that better captures what is inferred or by updating the parameters of the system's internal generative model to produce predictions that better reflect data (Friston et al., 2016: 864; Tabor & Burr, 2019: 55). The former alternative is introduced under active inference process. The latter is called active learning.

The inference of an action policy under active learning is for mitigating uncertainty about the system's model. Instead of fixing the model and changing its actions, as it is

the case for active inference, the model itself is updated in active learning. What updates the model is *information* in active learning process. In that sense, the inferred action policy is *exploratory*. Specifically, Bayesian optimal integration of the incoming *information* and the prior beliefs occurs over time to minimize the future prediction errors (Tabor & Burr, 2019: 56-7). That is, an active learner actively infers with increasing precision in future encounters (Clark, 2013: 10).

CHAPTER III

WHY DOES PHYSIOLOGICALLY ACUTE PAIN OUTLAST ITS PURPOSES TO TRANSFORM INTO PATHOLOGICALLY CHRONIC PAIN AND WHY IS PATHOLOGICALLY CHRONIC PAIN ACCOMPANIED BY PAIN AVOIDANCE BEHAVIOR?

Why physiologically acute pain outstays its functions to become pathologically chronic pain, and why pathologically chronic pain is accompanied by pain avoidance behavior remained elusive within the predictive processing framework. Essentially, in order to answer to these questions, I cast pathologically chronic pain and pain avoidance behavior as Bayesian probabilistic inference problems. Given that pain is a complex, convergent, and multidimensional experience, a Bayesian probabilistic model of pathologically chronic pain involves sensory, perceptual, affective, and motivational aspects. To date, the most researched feature of pathologically chronic pain within the predictive processing framework is established on perceptual inference. Following that, initially, I demonstrate what the perceptual inference account refers to regarding pathologically chronic pain. Up-to-date research holds that a complete understanding of pathologically chronic pain necessitates an explanation

of its motivational character, as well. However, when casting pathologically chronic pain and pain aversive behavior as Bayesian probabilistic inference problems, their motivational aspects call upon the explore-exploit dilemma and the emergence of active inference and active learning. In parallel, I call attention to the different levels of uncertainty and their influence on the emergence of active inference and active learning. Additionally, I show that different mechanisms are at work in gaining information and producing actions regarding pathologically chronic pain and pain avoidance behavior. Finally, I will propose that active inference and active learning lead to the emergence of pain avoidance behavior and pathologically chronic pain, respectively. Therefore, section 1 describes the influence of perceptual inference over pain. Section 2 lays out the key elements of the explore-exploit dilemma. Section 3 elaborates the implications of this dilemma on the unfolding of pathologically chronic pain and pain aversive behavior that accompanies pathologically chronic pain.

3.1 The Perceptual Inference Account of Pathologically Chronic Pain

Briefly, perceptual inference is a mechanism that functions in gaining information about the state that causes pain perception. What is inferred when pain is cast in terms of the perceptual inference is the cause of *nociception*. Perceptual inference is governed by the minimization of the mismatch between the encoded relative precisions of the incoming sensory data and the prior belief in the predictive processing framework. In parallel, this principle applies to pain encapsulating physiological, pathological, and nociplastic pain resulting in *nociceptive prediction error minimization*.

The research on the sensory aspect of pain, particularly, *nociception* goes back a long way. Pain perceptions generally involve nociceptive aspect, although it is not necessary for all pains. For example, some patients with pathological pains arisen from spinal cord injury, or some patients with nociplastic pains resulted from fibromyalgia do not have nociception. Yet, in the case of physiological pain, there is generally nociception. One exception is congenital insensitivity to pain, which causes the lacks of nociceptors and, in parallel, the encoding of nociceptive input to the model of a system or an agent (Woolf, 2010: 3742). What governs the physiological nociception is the minimization of the mismatch between the relative precisions of the physiological noxious input and the prior belief in the generative model of a system or an agent.

As to pathological pain, there is two directions to take. First, if there is not a nociceptive aspect of a particular pathological pain, then the perceptual inference account is insufficient to explain the pathological pain. Second, if there is a nociceptive character of a certain pathological pain, then the same principle—i.e., the prediction error minimization, applies. However, this is the tricky part. The reason is that the perceptual inference mechanism points to the presence of an underlying deficit in *precision optimization* within pathological pain. Specifically, the *prediction error* is a function of the relative uncertainties of beliefs resulted from the actual nociceptive cause and the prior encounters with the nociceptive source. It should be minimized over the long-term average. It occurs through *Bayesian optimal*

integration. That is, Bayesian optimal integration implies the nociceptive prediction error minimization. However, it is *biased*. It allows that the posterior nociceptive belief, which is formed via integration of the sensory information and the prior belief, biases toward either of them. It may bias towards the nociceptive evidence by either increasing the precision of nociceptive information and/or failing to attenuate it or decreasing the precision of the prior beliefs. Bayesian optimal integration indicates *nociceptive learning*. In other words, the nociceptive prediction error minimization means learning. If it occurs, then a system or an agent can *adapt to* the dynamically altering uncertain body and environment. However, *false nociceptive learning* may occur too. Having said that Bayesian optimal integration is biased, the precision of a nociceptive input may be *overestimated* and/or the precision of a prior may be *underestimated* or vice versa. This may result in the nociceptive posterior moves towards the sensory mean and away from prior mean. Through this, the predictive error minimization leads to *maladaptation* to the body or the environment or *false learning, false belief,* or *false inference*. That is to say that the nociceptive posterior belief may spend time *deviating* from the optimal nociceptive inference. This inference will manifest as *more or less transitory false nociceptive inference* or *entrenched false nociceptive inference*. As a result of the deviation from the optimal inference, it may fail to correct itself over time. This leads to *a cascading and increasingly ensconced malfunctions*. This refers to the *pathological condition*. As a result, this provides a ground for addressing how pathological pain perception is formed and maintained against counter perceptual evidencies. Given that the deviation from the optimal nociceptive inference requires time, the pathological pain

is maintained over time. The reason is that the reliance relatively more on nociceptive information leads to sampling and solving the uncertainties on the body and the environment *more and for longer time*. The deviation may entail time less than six months. In such a case, it may be referred as pathologically acute pain. However, if it endures more than six months or even a life time, then this may make it *pathological chronic pain*.

Analogous to pathologically chronic pain perception, many psychopathological disorders are associated with inappropriate beliefs about precisions of the prior beliefs and sensory information. That is, they are linked with entrenched false inferences. To exemplify, autism spectrum disorder has been related with higher prior expectation for the sensory precision (Van de Cruys, Evers, Van der Hallen, Van Eylen, Boets, de-Wit, & Wagemans, 2014). Particularly, a patient with autism spectrum disorder appeals relatively more to the senses than the priors with in the agent's hierarchical internal generative model's parameters (Hohwy, 2013: 161) Hallucinations in schizophrenia have been connected with higher prior expectations for the variations of the sensory input (Sterzer, Adams, Fletcher, Frith, Lawrie, Muckli, Petrovic, Uhlhaas, Voss, & Corlett, 2018). Delusions have been concomitant with false inference that is resulted from the reduction of the sensory precision in comparison with the prior precision (Adams, Brown, & Friston, 2014). Specifically, there is a heightened and continuous expectation for uncertain sensory data and increased and persistent reliance on the prior beliefs in both hallucinations in schizophrenia and delusions (Hohwy, 2013: 158). It is hypothesized that heightened chronic pain

expectation gives rise to heightened chronic pain perception (Hechler, Endres, & Thorwart, 2016).

3.2 Is Action Required for a Full-Fledged Account of Pathologically Chronic Pain?

If a system or an agent has settled on a posterior perceptual or nociceptive inference resulted in pathologically chronic pain, then why action should have a role in the system or the agent with pathologically chronic pain is a further inquiry. An answer may come from two different trajectories. If a pathologically chronic pain has a nociceptive aspect, then two supportive arguments in favor of action may be given. First, without action none of the beliefs of an agent can be favored strongly (Hohwy, 2013: 79). That is, action increases *the precision* and *the accuracy* of an inference encoded as a probability distribution. For example, suppose that one has happened to step on a lego piece in the middle of the night when she was trying to figure out the location of the light switch on the wall. The perceptual inference accounts for the noxious nociception caused by stepping on the Lego piece. She acts to minimize the following mismatch between the incoming sensory information—i.e., that there is *something* on the floor that may cause a damage on the body, and the prior inference—i.e., that the body integrity is intact. Many things can cause the exactly same inference. What causes this particular perception, which is a Lego piece, can be understood only by *pulling* her leg up, and *turning* her head down and *gazing at* the stuck piece on her foot.

Second, action is relatively more efficient than relying just on the perceptual inference (Hohwy, 2013: 80). In other words, to stay put for perceptions requires *time*, and it hereby is *inefficient* way to favor strongly an inference. For instance, one decided not take an action to turn the lights on and remained curious about what was the cause of noxious nociception perceived a couple of minutes ago in the middle of the midnight. Instead of carrying out an action to switch on the lights, she will wait the sunrise, thereby the sun light will fill the room and light the cause of nociception. This may take for hours. In contrast, switching on the lights takes just a couple of seconds. Therefore, active inference is relatively more efficient than the perceptual inference given a particular situation.

However, the second trajectory comes from where there is no nociceptive information. That is, if there is not a nociceptive aspect of a pathologically chronic pain (along with nociplastic pain), then what makes the pain pathological and chronic (or nociplastic) necessitates an account of action. Hence, the perceptual inference account of pathologically chronic pain is insufficient for its complete understanding. It fails to account for its motivational aspect.

What's more, the perceptual inference account of pain fails to account for the accompanying pain avoidance behavior. For instance, suppose one has a leg fracture due to falling on ice that may heal in three months. According to the perceptual inference, she will perceive a physiologically acute pain due to the fracture over this period of time. Especially, suppose that she perceives more pain when there is

pressure on the location of the fracture. Thus, she avoids leaning on her broken leg's side while sleeping to avert the perception of the physiologically acute pain. Suppose, further, that her perceptual inference deviated from its optimal precision and resulted in an entrenched pathologically chronic pain. Having said, she avoids to lean on her broken leg's side while sleeping to avert the perception of the pathologically chronic pain. Therefore, irrespective of whether this is a physiologically acute pain or a pathologically chronic pain, an account of action regarding pain is necessary.

3.3 The Explore-Exploit Dilemma: The Gap in the Pain Literature

When pathologically chronic pain, which has a motivational aspect, and pain avoidance behavior are cast in terms of Bayesian probabilistic inference problems, they call for a deep scrutiny of action within the predictive processing framework. Bayesian probabilistic internal generative models are characterized by *exploitative action* or *exploratory action strategies* (Figure 7). In parallel, active inference and active learning lead to attenuation or uplift of the exploration and exploitation strategies as functions of prediction error minimization over the long-term average (Hohwy, 2013: 71; Marković , Goschke, &Kiebel, 2020: 3). Particularly, the equilibrium between exploration and exploitation is governed by the minimization of uncertainty by means of active inference and active learning (Seymour & Mancini, 2020: 5). However, balancing exploration and exploitation brings along *the explore-exploit dilemma*. It refers to knowing when to switch to exploitation of learned information, and to pause exploring for new information about an ever-changing and uncertain environment, and vice versa (Marković et al., 2020: 2). That is, if a certain

action yields prosperous surprise minimization, then how long the action should be prolonged culminates in the dilemma. Specifically, if the action perpetuated, then the system or agent would never know if the action is necessitated indefinitely within the environment, or if the cause of the action has otherwise ceased (Schwartenbeck, Passecker, Hauser, FitzGerald, Kronbichler & Friston, 2019: 1).

Exploitative actions are *outcome-driven actions* (Friston et al., 2016: 863). That is, they are the best actions that result in the best outcomes based on the present beliefs about the environment (Schwartenbeck et al., 2019: 1). In this respect, they are pragmatic and susceptible to risks (Seymour & Mancini, 2020: 5).

Contrarily, exploratory actions are *information-driven actions* (Friston et al., 2016: 863). In other words, they are the actions that yield information about whether there are any better action whose outcome is partially or fully unknown at present (Schwartenbeck et al., 2019: 1). In this sense, exploratory actions are epistemic and susceptible to ambiguity (Friston et al., 2016: 863).

There are two kinds of exploratory strategies: *goal-directed* and *random* exploration (Friston et al., 2016: 863). Goal-directed or directed exploration is motivated by *uncertainty* within a system's model of the environment based on either the uncertain mapping from a state to an outcome or an uncertain state (Schwartenbeck et al., 2019: 2). This entails that the system samples information that is held with the highest uncertainty (Schwartenbeck et al., 2019: 2). In addition to that, the goal-directed

exploration adds *cost, noise, or bonus* to policy that is arbitrarily chosen due to the highest uncertainty (Kakade & Dayan, 2002: 554).

Here it is important to note that there are two types of *uncertainty* or *surprise, which are unexpected uncertainty* and *expected uncertainty* (Schwartenbeck et al., 2019: 2). Unexpected uncertainty refers to *ambiguity*, whilst expected uncertainty refers to *risk* (Figure 8). In parallel, an exploitative policy is sensitive to expected uncertainty, whereas an exploratory policy is sensitive to unexpected uncertainty. Essentially, for a system, it is necessary to tackle with an ambiguity before tackling with a risk of a policy (Schwartenbeck et al., 2019: 2).

There are, also, two types of goal-directed exploration: *the hidden state exploration* (Figure 7B), and *the model parameter exploration* (Figure 7C). Goal-directed ambiguity reduction relies on the mapping between the hidden state and the observation. That is, a system must infer both the action policy and the current hidden state that causes the observation.

If the mapping from underlying a hidden state to an outcome is unambiguous, then the system can navigate to the outcome. This implies that the system can actively sample until it achieves the outcome, which has unambiguous mapping to the hidden state (Figure 9). In other words, the hidden state exploration can occur through *active inference* (Schwartenbeck et al., 2019: 2). Active inference ensures the hidden state exploration by driving a system to actively look for *already learned or known salient*

outcome that provides an inference of the hidden state unambiguously (Schwartenbeck et al., 2019: 5; Tabor & Burr, 2019: 56). For example, suppose that one flips a certain coin and always observes heads. Additionally, one has learned previously that a loaded coin always shows heads, and a normal coin shows a mixture of heads and tails when it is flipped a number of times. Thus, the mapping from the hidden state to the observation is unambiguous. In parallel, suppose that her inference is to observe heads if she flips it one more time. The hidden state that causes this observation and inference may result from that this certain coin is a loaded one. Yet, the hidden state can be just luck, as well. In this scenario her expected uncertainty is based on that this certain coin is loaded. Contrarily, her unexpected uncertainty is based on the idea that the observation of heads is due to mere luck. Her inference will be that if they rely on luck, then the coin will show tails at least one time; and if they are because of coin's being loaded, then the coin will show heads all the time. In order to minimize the unexpected uncertainty, her inferred policy will be to flip the coin multiple times. Suppose that she observes heads irrespective of the number of times flipping the coin. Thus, she infers that the coin is actually a loaded coin.

However, if a system is ignorant about the mapping of its model, then the system acts in order to learn its model's previously unexplored contingencies. That is , if in a goal-directed exploration, a system needs to reduce not only the uncertainty about the current hidden state, but also the uncertainty of the mapping between the hidden state and an outcome along with inferring the best action policy that is uncertain at present to achieve the uncertainty reduction, then it is model parameter exploration (Figure

9). It occurs through *active learning* (Schwartenbeck et al., 2019: 5). Active learning assures the model parameter exploration by compelling a system to actively try out *novel* combinations of the hidden states and outcomes in order to actively learn about the mappings, in which the outcomes are guaranteed (Schwartenbeck et al, 2019: 7; Tabor & Burr, 2019: 55). To exemplify, suppose one wants to make soft chocolate chip cookies. Yet, suppose that she has a knowledge gap concerning the recipe of soft chocolate chip cookies. Particularly, she is uncertain about whether adding too much or not enough flour makes a chocolate chip cookie soft. Additionally, suppose that she is not certain concerning whether over-beating or under-beating the eggs produces soft chocolate chip cookies. Moreover, suppose that she has not learned whether she should melt the butter or she should not melt the butter for soft chocolate chip cookies. In this setting, her mapping from the hidden state, which is the recipe, to the observation, which is the softness of the chocolate chip cookies, is ambiguous. That is, these contingencies are associated with the highest uncertainties. To fill her knowledge gap— to learn and minimize the uncertainties, her inferred policy will be to actively try out novel combinations of the amounts of flour, egg-beating, and butter-melting.

Additionally, for active learning to occur there must be *stable regularities* or *rules* in an environment that can be learned (Figure 9). That is, active learning refers to being able to carry information from one trial to the next. This is provided by the regularities or rules in an environment. Further, active learning occurs over time. In that sense, it is a slow way to reduce uncertainty. Contrarily, active inference can

often be a faster way of reducing uncertainty (Schwartenbeck et al., 2019: 25). In the cases where active learning is broken and it is possible to calculate uncertainty, active inference can reduce uncertainty instead of active learning.

In contrast to goal-directed exploration, *random* or *undirected exploration* (Figure 7A) is directed to randomly sampling information regarding the altering and uncertain environment while diverging from the best action already learned given the current beliefs (Schwartenbeck et al., 2019: 1). This entails that a randomly exploratory action is not informed by a system's uncertainty regarding a hidden state or its mapping (Schwartenbeck et al., 2019: 8). Importantly, random exploration can allow a divergence from the currently best action policy whose outcome is fully and certainly known. It also occurs through active inference. This implies that such an action will not decrease uncertainty per se but may cause accidental belief updating or learning due to random or stochastic selection of different policies. In this regard, random exploration may have an adaptive function in the absence of goal-directed exploratory actions that may be a result of a system's inefficacy to calculate uncertainties—i.e., active inference and/or learning is broken (Schwartenbeck et al., 2019: 10, 25).

Therefore, goal-directed exploration can refer to either exploring the hidden state that causes the outcome or exploring the parameterization of the system's model. Concurrently, gaining information and uncertainty minimization can be achieved by either active inference or active learning. In other words, the exploration of the hidden

state is called active inference, whereas the exploration of the model parameterization is called active learning. Furthermore, in the lack of goal-directed exploration, random exploration may result in adaptive learning.

Importantly, inferences made through hidden state exploration by active inference and through model parameter exploration by active learning can either support or oppose each other (Schwartenbeck, 2019: 5). If there are regularities and/or rules within a system's environment that are *stable* enough in order to be learned through time by a system, then the hidden state exploration can be cast in terms of active learning. In this setting, the prediction made through hidden state and model parameter exploration boost each other (Schwartenbeck et al., 2019: 24). However, if the context changes *randomly*, then the hidden state exploration is cast in terms of active inference and may contradict with an inference made by active learning. That is, the minimization of surprise by means of model parameter exploration may produce an action that opposes the minimization of uncertainty through hidden state exploration when there is high ambiguity or novelty (Schwartenbeck et al., 2019: 25). Particularly, if an outcome is ambiguous due to the ambiguity in a system's mapping from a hidden state to its outcome, then the system infers that this is highly interesting and can be actively learned. Nevertheless, given that the outcome is ambiguous, it is highly aversive from the active inference perspective. For instance, suppose that one decided to watch a sci-fi movie she will enjoy, and what she got is The Matrix, The Matrix Reloaded, and The Matrix Revolutions. Suppose that she saw the Matrix and The Matrix Reloaded and really enjoyed the prequel. Additionally, suppose that she

has previously learned that the sequels are never better than the prequels. In this context, which movie should she choose? Given that she saw the first two movies, there is an unambiguous mapping from the hidden state—i.e., a movie, to the outcome—i.e., enjoyment and a prior belief that the prequels are the best. Her inferred action would be to choose The Matrix over The Matrix Reloaded since she would achieve the outcome through the hidden state exploration. Therefore, active inference results in that she should re-watch The Matrix. However, there is a novel, interesting, and informative option, which is The Matrix Revolutions. In parallel, in her mapping of the structure of the environment, there is a knowledge gap due to the ambiguous mapping that can be filled with model parameter exploration. Thus, active learning leads to that she should watch The Matrix Revolutions.

3.4 The Active Learning Account of Pathologically Chronic Pain and The Active Inference Account of Pain Avoidance Behavior

So far, I have referred to the perceptual inference account of physiologically acute pain and pathologically chronic pain that was held until recently. After the progress in the predictive processing literature capturing the intertwinement of perceptual inference and active inference, I have touched on the latest well-establishment of the influence of action in the literature of pain. The up-to-date challenge is the position of the active learning within the framework and its contributory effect on pain. In connection with this, Tabor and Burr (2019) suggest that pathologically chronic pain is formed due to precision weighting of noxious information that eventually leads to the learned optimal precision weighting over time, and that informs a system's model

to explore or exploit its environment. Nevertheless, when the tables are turned, this paper does not elaborate on the offerings of the explore-exploit dilemma through active inference and active learning to the emergences of persistent pain and pain avoidance. In order to pave the way for my research, I have pointed out to the exploration-exploitation dilemma within the predictive processing framework, as well. Thus, the question that I investigate here is exactly how active inference and active learning play role in the formation, maintenance and treatment of pathologically chronic pain and pain avoidance behavior. The main motive lurking behind my current inquiry is that to track down the reason causing that physiologically acute pain outwears its purposes to convert into pathologically chronic pain. Additionally, to figure out the ground for the arise of concomitant pain avoidance is another motive of this analysis.

Active inference and active learning lay out a general ground for understanding a system's exploitative and exploratory actions (Schwartenbeck et al., 2019: 35). Following that, active inference and active learning mechanisms promise a clarified understanding of *goal-directed cognitive deficits* within the scope of psychopathological conditions (Schwartenbeck et al., 2019: 26). Further, the trade-off between exploitative actions and exploratory actions lies at the heart of pain, especially pathologically chronic pain and pain avoidance actions.

Particularly, the interchange among hidden state exploration, model parameter exploration, random exploration, and exploitation is governed by their relative

precisions. Their relative certainties are products of the prediction error minimization, since prediction error is a function of their uncertainties. Therefore, the trade-off between them is governed by minimization of uncertainties. In parallel, when pathologically chronic pain and pain avoidance behavior are casted as Bayesian probabilistic inference problems, they are guided by the minimization of uncertainties. Therefore, the minimization of uncertainty is closely linked with pathologically chronic pain and pain avoidance behavior. In parallel, the trade-off between hidden state exploration, model parameter exploration, random exploration, and exploitation is closely linked with pathologically chronic pain and pain avoidance actions.

However, they may result in contrasting actions when an action policy is highly interesting and novel due to its high ambiguity and, at the same time, it is highly aversive because of the same reason—i.e., its ambiguity of the outcome. That is, if the outcomes of a policy are ambiguous respective of high ambiguity about the mapping between the policy and the outcome, then the policy is highly informative. However, if the system is certain regarding that the outcomes of the policy are ambiguous, then the same policy is highly aversive. Importantly, the ambiguity in the mapping of the system must be resolved before the resolution of the uncertainty about the outcomes. Hence, the uncertainty about the model parameterization modulates the effect of uncertainty regarding hidden states on action (Schwartenbeck et al., 2019: 25).

On top of these, I propose that, in the case of pathologically chronic pain, its formation and maintenance result from active learning, while accompanying pain avoidance behavior results from active inference. Consider the following argument.

(i) Pathologically chronic pain is a pain experience that originates from a disease or an injury, and lasts for a long time irrespective of the endurance of its cause. (Ass.)

(ii) Pain avoidance behavior is the development and the maintenance of aversion to certain actions to refrain from inducing pain. (Ass.)

(iii) Pathologically chronic pain and pain avoidance behavior involve goal-directed exploratory action strategies because the goal that directs them is to minimize unexpected uncertainty—i.e., ambiguity. (Ass.)

(iv) A system or an agent with pathologically chronic pain has biological alterations, which work as stable regularities, within her mappings between the hidden states and their outcomes because of a past disease or injury. (Ass.)

(v) If it is uncertain that the outcome of a goal-directed exploratory policy will result in pain due to high ambiguity regarding the agent's mapping between the hidden state and the outcome, then this policy is highly informative, interesting and novel—i.e., the model parameter exploration. (Ass.)

(vi) Active learning is updating the parameters of a system or an agent’s generative model to produce inferences that better reflect the incoming information. (Ass.)

(vii) Therefore, pathologically chronic pain involves the model parameter exploration. The mapping of the system or the agent with pathologically chronic pain gets certain gradually through active learning. (i, iii, iv, v, vi)

(viii) If it is uncertain that the outcome of a goal-directed exploratory policy will result in pain, and the agent's mapping from the hidden state to the outcome is unambiguous; then this policy is highly aversive. (Ass.)

(ix) Active inference is carrying out actions to sample input that better captures what is inferred either for epistemic purposes or achieving an outcome. (Ass.)

(x) Therefore, pain avoidance behavior originates as the hidden state exploration through active inference. (ii, iii, viii, ix)

(xi) Therefore, the uncertainty in the outcomes of an action policy and the uncertainty in the generative model result in the emergence of pathologically chronic pain and pain avoidance behavior. Pain avoidance behavior accompanies pathologically chronic pain. (v, vii, viii, x)

(xii) Physiologically acute pain is a nociceptive or inflammatory experience that originates from a disease or an injury, and lasts for a short time with reference to the agent's gradual healing, which indicates no new stable regularities laid out biologically. (Ass.)

(xiii) The action occurs as a result of physiologically acute pain involves exploitative action strategy. (Ass.)

(xiv) If there is high ambiguity regarding the agent's mapping between the hidden state and the outcome in addition to that active inference is broken due to a disease or an injury, which resulted in physiologically acute pain, then through active learning new biologically stable regularities (i.e., brain plasticity) are formed and physiologically acute pain turns into pathologically chronic pain. (Ass.)

(xv) Therefore, the trade-off among the model parameter exploration, the hidden state exploration, and the exploitation is governed by the uncertainty minimization within the predictive processing framework. (vii, x, xiii, xiv)

(xvi) Pathologically chronic pain and its accompanying pain avoidance behavior are psychopathological conditions. (Ass.)

(xvii) Therefore, active inference and active learning mechanisms promise a clarified understanding of the goal-directed cognitive deficits within the scope of psychopathological conditions. (xii, xvi)

Phantom limb pain can be given as an exemplificatory case. Phantom limb pain is modulated by the model parameter exploration. That is, after an amputation, the generative model of an system or an agent incorporates in uncertainty regarding her model of her body. In order to minimize the uncertainty, it is expected that the amputee will engage in the model parameter exploratory activities through active learning. This will allow her to convey what she learnt in one occasion to the next so that she may exploit via active inference this information in the future. However, the

exploitative action strategies may not work all the time. The reason of this is that the generative model of the amputee will keep altering because of brain's plasticity. This manifests that there is not stable biological regularities. This will motivate the amputee to take exploratory action strategies. The shift back and forth between the model parameter exploration and exploitation continues indefinitely.

Further, the pathologically chronic phantom limb pain is accompanied by pain avoidance behavior. After the minimization of the uncertainty in the mapping of the amputee's generative model as much as it is possible, whether the outcome of an action is painful or not may be ambiguous. Therefore, this action policy will be interpreted as aversive resulting in pain avoidance behavior.

3.5 The Future Directions

The thesis paves the way for three future directions in distinct disciplines such as philosophy, neuroscience, and medicine. First, given that pain is a complex experience, its modulators also enclose thought, beliefs and desires. They may have impacts on the emergence, maintenance, and management or treatment of pathologically chronic pain. Hence, the predictive processing framework is required to explain such propositional mental states (Williams, 2020).

Second, although the computational approaches to cognition have a convincing advantage over the neuroscientific approaches to cognition, the neural underpinning of the computational activities in the human brain is necessitated for a full-blown

apprehension of cognition. In parallel, the brain oscillations and the synchrony at different frequencies may provide further evidence on information flow across areas of the human brain, which underlies the computational processes.

The neuroscientific approach to cognition combined with the prediction error framework hypothesizes that the information refers to the predictions and the prediction errors (Ploner, Sorg & Gross, 2017). *Beta (12-30 Hz) frequency* reflects *the prior predictions* and takes role in feedback signaling in the descending pathway of pain (Arnal & Giraund, 2012). Further, *the prediction errors* are reflected by *gamma (30-100Hz)* frequency and serves feedforward signaling in the ascending pathway of pain (Pinheiro, Queirós, Montoya, Santos, Nascimento, Ito, Silva, Nunes Santos, Benevides, Miranda, Sá & Baptista, 2016). In the pathologically chronic pain cases, there is an abnormal increase in *theta (4-8 Hz) frequency* (Stern, Jeanmonod & Sarnthein, 2006; Sarnthein, Stern, Aufenberg, Rousson & Jeanmonod, 2006), however its role in the predictive processing framework has not been refined yet. It may be hypothesized that theta frequency refers to posterior inference concerning pathologically chronic pain.

Third, having said that pain is fundamentally about action, the cognitive behavioral therapy (CBT) may promise noteworthy pain treatment methods. CBT is a kind of therapy that lies at the intersection of multiple disciplines such as psychology, psychiatry, pharmacology, and so forth (Tang, 2018). Its theoretical basis is on the learning models such as the classical Pavlovian (habitual) conditioning, the operant

(instrumental) conditioning, Rescorla-Wagner learning, associative learning, and so on (Tabor & Burr, 2019: 54). It adds the influence of beliefs and appraisals in the learning models. In addition, it recognize the effect of behavior on psychological responses. In parallel, the psychopathological conditions such as pathologically chronic pain can be treated by means of CBT. However, it necessitates that these learning models and active learning must find a middle ground.

CONCLUSION

In this thesis, I disputed that the computational approaches like the predictive processing have a great advantage over the neuroscientific approaches when it comes to an efficient understanding of the human brain. Peculiar as is pain, I held that pain is worthy to be studied philosophically because (*i*) it is not fully biochemically explicable, (*ii*) it is not objectively identifiable, and (*iii*) it is not treatable but manageable according to what is currently known. Additionally, I made cases for evaluativism, imperativism, and psycho-functionalism regarding their explanatory power on pain. Yet, all three failed at different points. Further, I argued that the predictive processing framework holds out high hopes of refined comprehension of the goal-directed cognitive deficits within the scope of psychopathological conditions such as pathologically chronic pain and pain avoidance behavior. Particularly, I revolved around the questions (*I*) why physiologically acute pain overstays its protective function to become a pathologically chronic pain and (*II*) why pain avoidance behavior accompanies pathologically chronic pain. I made use of the explore-exploit dilemma to respond these inquiries. I inferred that (*1*) pathologically chronic pain comprises the model parameter exploration through active learning, (*2*) pain avoidance behavior involves the hidden state exploration through active inference, (*3*) physiologically acute pain results in exploitative action. I proposed that (*a*) the very same uncertainty in outcomes of an action strategy entails both

pathologically chronic pain and pain avoidance behavior, and (*b*) the high ambiguity in a system or an agent's internal mapping between hidden states to outcomes and the broken active inference because of a disease or an injury entail the transformation of physiologically acute pain to pathologically chronic pain. Thus, pain avoidance behavior accompanies pathologically chronic pain, and physiologically acute pain leaves its protective and adaptive purposes to turn into non-protective and maladaptive pathologically chronic pain. Moreover, the thesis has three future directions: (*A*) the predictive processing framework may bring forward an account for thoughts, beliefs, and desires, which modulate pathologically chronic pain, (*B*) the brain oscillations such as *theta* and the synchrony at different frequencies may require an investigation and may offer further evidence on information flow across areas of the human brain with pathologically chronic pain, (*C*) CBT may assure pathologically chronic pain treatment, if the learning models grounding CBT and active learning underpinning the predictive processing framework needs to settle a dispute.

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APPENDIX

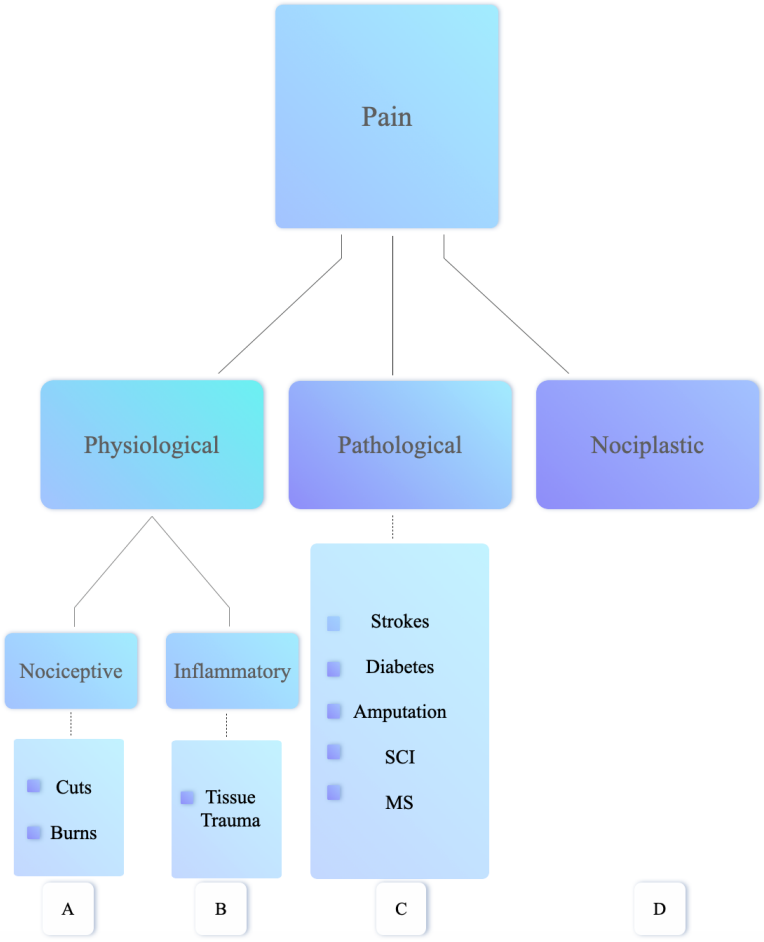

Figure 1. The classification of pain based on causes. Mainly, there are three kinds of pain: physiological pain, pathological pain, and nociplastic pain. Physiological pain has two sub-types: nociceptive pain (A), and inflammatory pain (B). Nociceptive pain results from cuts, fire burns, or ice burns. Inflammatory pain originates from tissue trauma that results in inflammation. Pathological pain stems from injuries or diseases such as strokes, diabetes, amputations, spinal cord injuries, or multiple sclerosis (C). Nociplastic pain such as fibromyalgia arises from no particular reason (D).

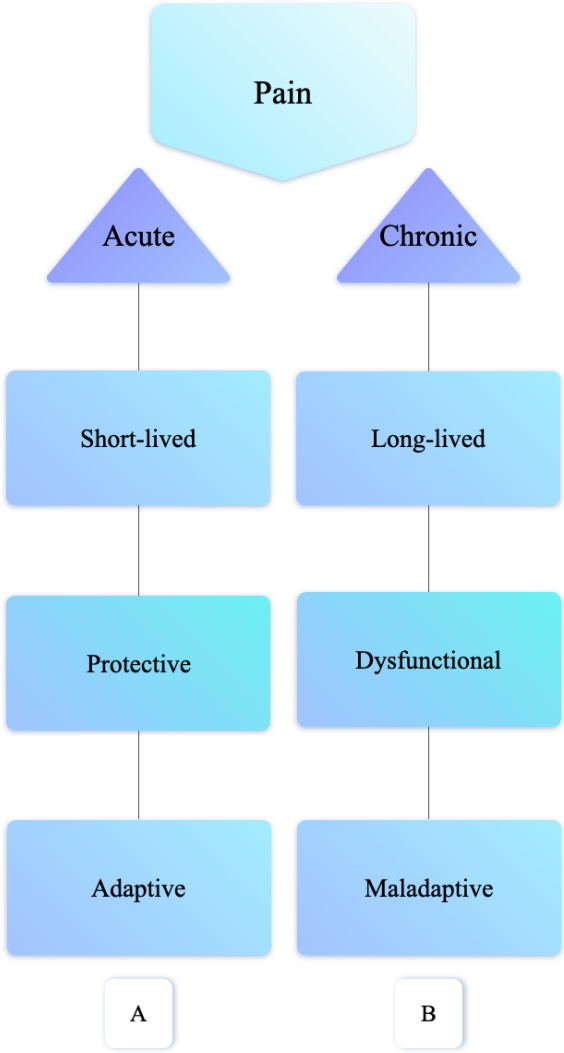

Figure 2. The classification of pain based on persistency. Pain is either acute or chronic. What makes a pain acute are that it lasts less than six months-i.e., short-lived, that it has a function in protection of the bodily integrity, and that its function is an adaptation that results in the survival of a system or an agent (A). Contrarily, what makes a pain chronic are that it lasts more than six months or a life time, that it lacks function in the survival of a system or an agent, and that it is a maladaptation of a system or an agent (B).

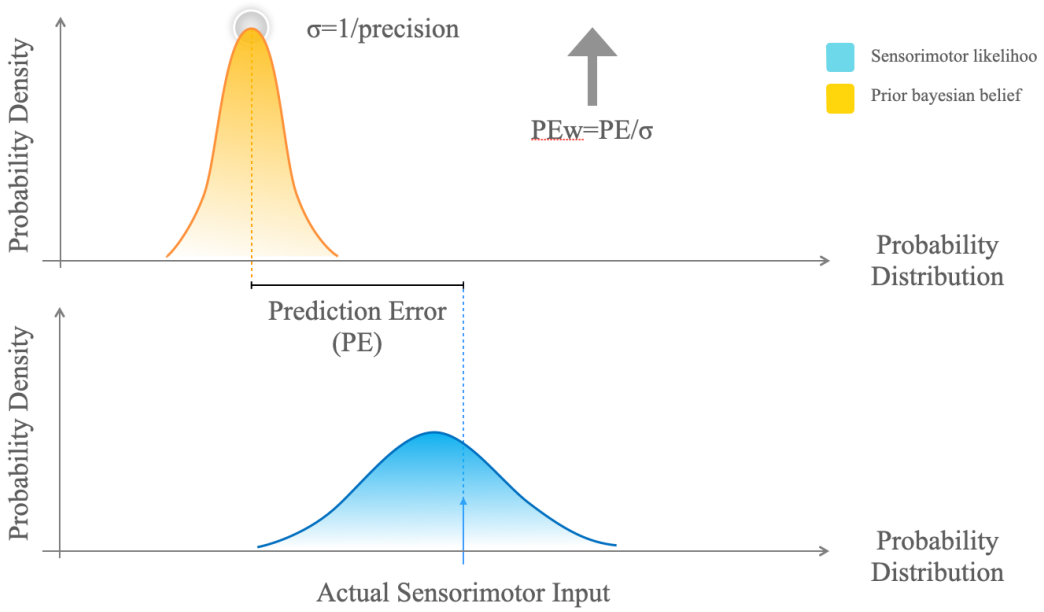

Figure 3. The key elements of Bayesian Brain Hypothesis. Beliefs or inferences are statistical probability distributions over the unknown sources of states. A prior belief is a belief that is encoded prior to a sensorimotor information. A sensorimotor likelihood is a current sensorimotor information. Sensorimotor likelihood is noisy information. A prior belief that will match with a sensorimotor likelihood has also a subjective uncertainty. The difference between the precision of a prior belief and the precision of the actual sensorimotor input refers to the precision of prediction error (PE). The precision of the prediction error is weighted and set off for the formation of a refined belief called a posterior belief.

Figure 4. The influence of precise source of information on posterior belief. The relative precisions of the prior belief and the sensorimotor likelihood contribute to the precision of the posterior belief. If an inference is relatively more precise, then it has a greater impact on the formation of the posterior belief. The precision of an inference is shown as relatively more narrower probability density. For example, the precision of the sensorimotor likelihood remained as constant, if the precision of the prior belief is relatively higher than the precision of the sensorimotor likelihood, then the prior belief contributes more in the formation of the posterior belief, and the probability density of the posterior belief is drawn toward the prior belief (A). However, if the precision of the prior belief is relatively lower than the precision of the sensorimotor likelihood, then the the sensorimotor likelihood contributes more in the formation of the posterior belief, and the probability density of the posterior belief is drawn toward the sensorimotor likelihood (B).

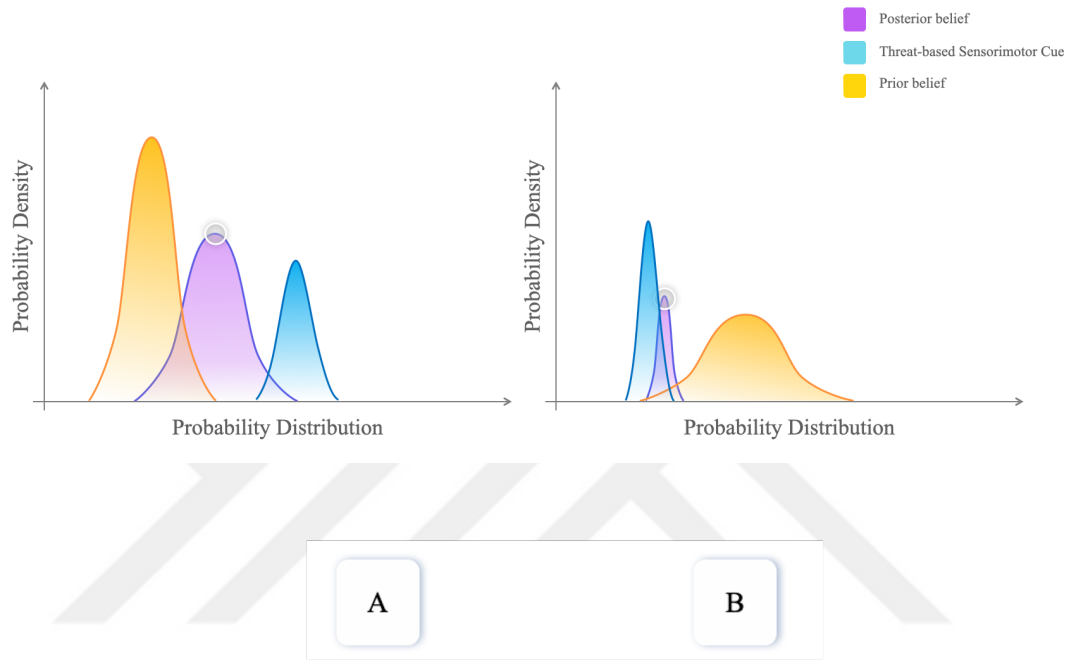

Figure 5. The decoupling of the actual sensorimotor information from the subjective experience of a system or an agent. Within the predictive processing framework, there is a decoupling between an actual sensorimotor information and a prior belief of a system or an agent. Suppose that there is an actual threatening sensorimotor information in the environment. If there is a relatively precise prior belief that reflects the bodily integrity and safety of the system or the agent, then although there is a threatening current sensorimotor information, the posterior belief, influenced more by the prior belief, reflects the bodily integrity and safety (A). Contrarily, the prior belief is relatively less precise than the relative precision of the sensorimotor likelihood, then the posterior belief is relatively closer to the sensorimotor likelihood, and it reflects the threat towards the bodily integrity (B).

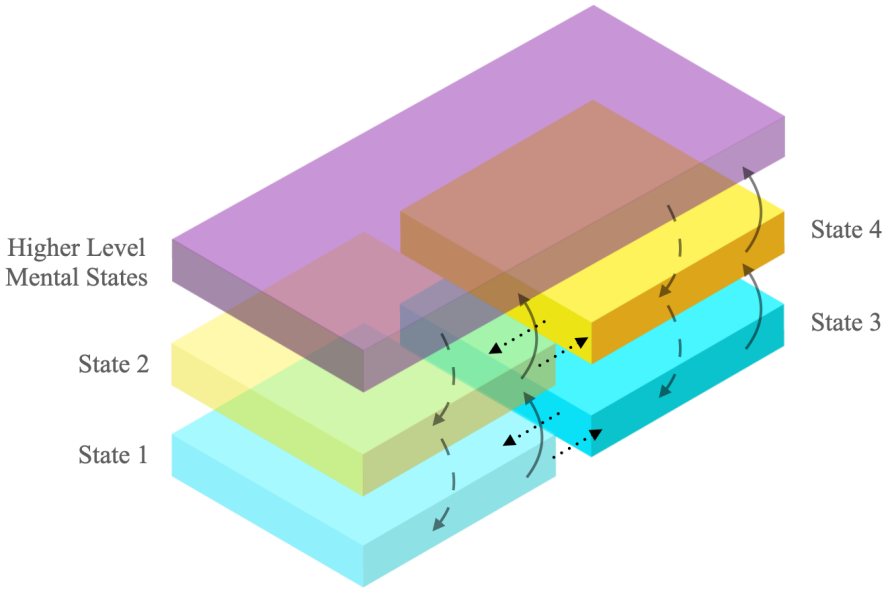

Figure 6. The hierarchical probabilistic internal generative model. It generates inferences that results from the hidden external states, and, even, in the absence of its external stimulation by the hidden states. It is formed over time to reflect a precise representation of the body and the environment. There is a hierarchy of inferences. The prior beliefs are generated by the relatively higher mental states. The sensorimotor likelihoods are created by the relatively lower mental states, and they carry weight towards the relatively higher mental states because of the mismatch between the sensorilikelihoods and the priors.

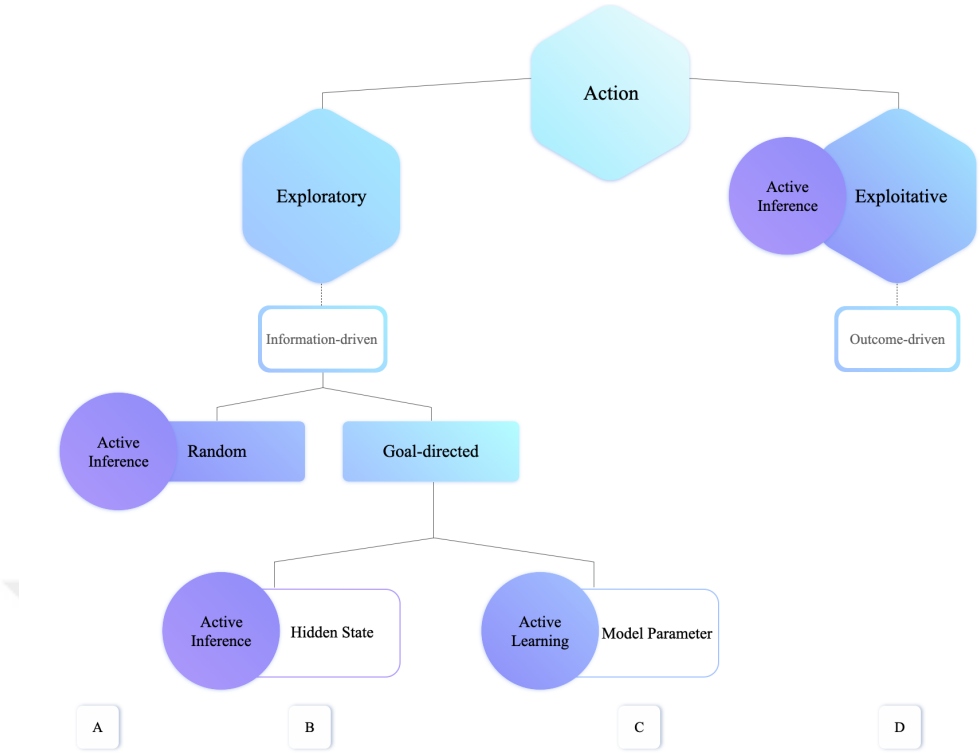

Figure 7. The classification of action strategies. Mainly, there are two types of action strategy: exploratory action strategy and exploitative action strategy. An exploratory action policy is information-driven. That is the role of an exploration is to gain information. There are two sub-types of exploration: random exploration and goal-directed exploration. A random exploratory action policy is to randomly sample information that is available in the body and the environment, which results in updating in the generative model of a system or an agent. It occurs through active inference (A). There are two kinds of goal-directed exploration: the hidden state exploration and the model parameter exploration. The hidden state exploration is to gain information about the source of a sensorimotor information that causes an observation by means of active inference (B), whereas the model parameter exploration is to gaining information for generating the mapping from a hidden state to its observation through active learning (C). In contrast, an exploitative action policy is outcome-driven. That is, it occurs to achieve a certain observation via active inference (D).

Figure 8. The classification of uncertainty kinds. Mainly, there are two kinds of uncertainty: expected uncertainty and unexpected uncertainty. The expected uncertainty stands for risk, while the unexpected uncertainty refers to ambiguity. Exploitative action strategy is sensitive to risk (A). However, exploratory action strategy is sensitive to ambiguity (B).

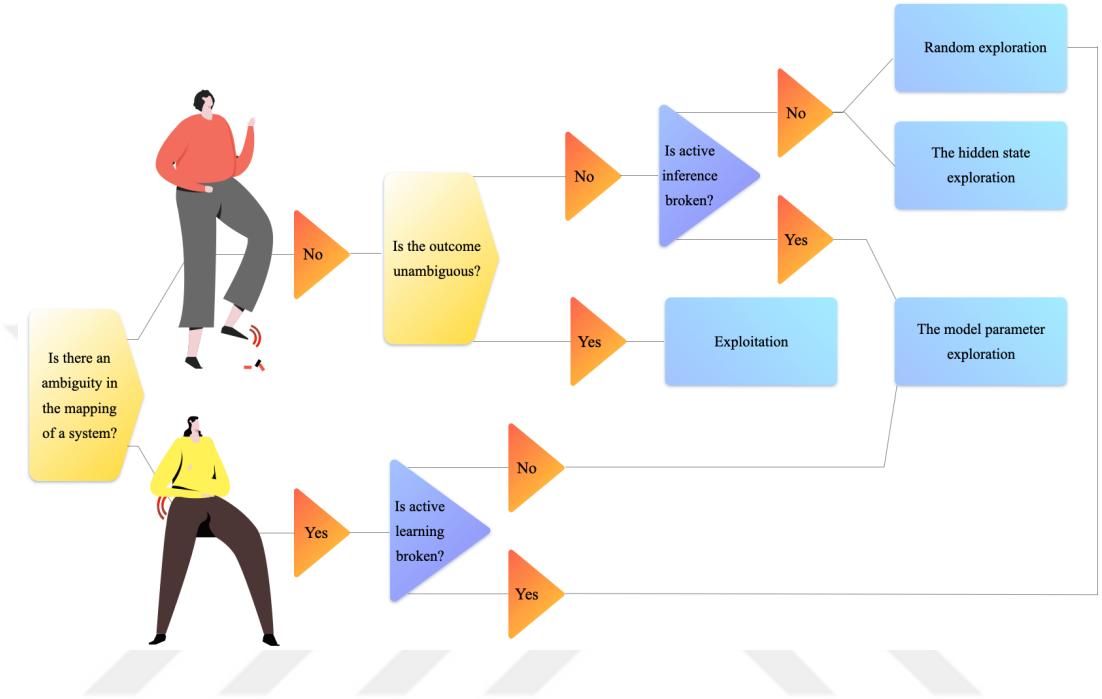

Figure 9. The trade-off among the action strategies. Whether there is an ambiguity within a system or an agent's model's mapping from a hidden state to an observation or not, and whether the observation is ambiguous or not determine the system or the agent's action policy. Additionally, whether the ability of the system or the agent to make an active inference or to do active learning has influence over the trade-off among the action strategies. For instance, active learning may be broken by the lack of stable regularities in the body and the environment. As another example, active inference may be broken by the lack of activity in a certain body part. In parallel, stepping on lego pieces may need to the hidden state exploration for the observation of the lego pieces on the floor, while multiple sclerosis may need to the model parameter exploration for the precise representation of the current body form.

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> 3**A Master's Thesis by** EYŞAN DEMİRKAYA **Department of Philosophy İhsan Doğramacı Bilkent University Ankara May** 2021 **To**

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> 2**Graduate School of Economics and Social Sciences of İhsan Doğramacı Bilkent University by** EYŞAN DEMİRKAYA **In Partial Fulfillment of the Requirements for the Degree of MASTER OF ARTS IN PHILOSOPHY THE DEPARTMENT OF PHILOSOPHY İHSAN DOĞRAMACI BİLKENT UNIVERSITY ANKARA May** 2021 **I certify that I have read this thesis and have found that it is fully adequate, in scope and in quality, as a thesis for the degree of Master of** Arts in **Philosophy**. ---------- Asst. **Prof**. István Albert Aranyosi **Supervisor**, Bilkent University, **Department** of Philosophy **I certify that I have read this thesis and have found that it is fully adequate, in scope and in quality, as a thesis for the degree of Master of**

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> 11**Approval of the Graduate School of Economics and Social Sciences ---------- Prof. Dr**. Refet Soykan Gürkaynak **Director ABSTRACT** PATHOLOGICALLY CHRONIC PAIN **AND**

PAIN AVOIDANCE BEHAVIOR WITHIN PREDICTIVE PROCESSING FRAMEWORK Demirkaya, Eyşan

> 5**M.A., Department of Philosophy Supervisor: Asst. Prof. Dr. István Albert Aranyosi June** 2021 Pain as **the**

most enquired philosophical theme is a complex experience, which includes sensation, emotion, motivation, cognition, and social interaction. However, there is not a single overarching philosophical theory that accounts for all the dimensions of pain. The most overlooked discussion of pain is on its motivational aspect; yet, it is indispensable for an integrated understanding of pain. Also, its least debated area is the

substantial relation between pathologically chronic pain and action. In this thesis, I attempt to investigate why physiologically acute pain outlasts its purposes to transform into pathologically chronic pain and why pathologically chronic pain is accompanied by pain avoidance behavior by drawing inferences from the explore-exploit dilemma. I also examine the related pain theories addressing their i failures in answering these questions. I conclude that analyzing pathologically chronic pain and pain avoidance behavior within predictive processing framework (1) provides an active learning account for pathologically chronic pain, (2) ensures an active inference account for pain avoidance behavior, (3) allows an active learning account for pain avoidance behavior only if certain conditions are met, and (4) points out the disparate action strategies are accountable for pathologically acute pain, pain avoidance behavior, and physiologically acute pain. Keywords: Active Inference, Active Learning, Explore-Exploit Dilemma, Pain Avoidance Behavior, Pathologically Chronic Pain ii ÖZET ÖNGÖRÜYE DAYALI İŞLEME ÇERÇEVESİ İÇİNDE PATOLOJİK KRONİK AĞRI VE AĞRIDAN KAÇINMA DAVRANIŞI Demirkaya, Eyşan

4**Yüksek Lisans, Felsefe Bölümü Tez Danışmanı: Dr. Öğr. Üyesi István Albert Aranyosi**

Haziran 2021 Ağrı, en çok araştırılan felsefik temalardan biri olarak, algı, duygu, motivasyon, biliş ve sosyal etkileşimleri içeren kompleks bir deneyimdir. Fakat ağrının tüm boyutlarını kapsayan bir felsefe teorisi bulunmamaktadır. Ağrı tartışmalarında en çok gözardı edilen ağrının motivasyon boyutudur; bununla birlikte motivasyon, ağrının bütüncül bir anlayışı için temel bir bileşendir. Ayrıca, ağrının motivasyon yönünün en az tartışılan alanı patolojik kronik ağrı ile eylem arasındaki önemli ilişkidir. Bu tezin esas amacı fizyolojik akut ağrının fonksiyonlarını kaybederek neden patolojik kronik iii ağrıya dönüştüğüne ve ağrıdan kaçınma davranışının patolojik kronik ağrıya neden eşlik ettiğine keşfet-faydalan ikileminden çıkarımlarda bulunarak cevap aramaktır. Bu tez aynı zamanda ilgili ağrı teorilerini ve onların bu soruları cevaplamadaki başarısızlıklarını inceleyecektir. Bu tezden çıkarılan sonuçlara göre, öngörüye dayalı işleme çerçevesi (1) patolojik kronik ağrıyı aktif öğrenme ile açıklar, (2) ağrıdan kaçınma davranışını aktif çıkarım ile izah eder, (3) ağrıdan kaçınma davranışını yalnızca belirli koşullar sağlandığında aktif öğrenme ile ifade eder ve (4) farklı eylem stratejilerinin patolojik kronik ağrıdan, ağrıdan kaçınma davranışından ve fizyolojik akut ağrıdan sorumlu olduğuna işaret eder. Anahtar Kelimeler: Ağrıdan Kaçınma Davranışı, Aktif Çıkarım, Aktif Öğrenme, Keşfet-Faydalan İkilemi, Patolojik Kronik Ağrı

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39**One approach to this question is to** scan the **brain**

, which, falls into the scope of neuroscience. Scanning is a way of producing the detailed images of the human brain by the magnetic fields and radio waves (MRI and fMRI) or X-rays (CT) or electrical charges (EEG) (Glover, 2011). Yet, these scanning techniques are not nearly good enough to capture all the activities in the human brain. There are two reasons for this situation. Initially, there are technical challenges in scanning such as noise signals, image distortions, and signal dropouts. Secondly, the human brain is complex. There are approximately

30**100 billion neurons in the human brain** while these **are in**

communication with one another through one million billion synapses ("Brain Facts and Figures", 2021). Signals are fired reaching to one thousand times every second. This implies that up to one quadrillion signaling events occur each second. What's more, there is a lot more to the human brain than the neuronal cells and signals. There are 10- to 50-fold more non-neuronal cells including the glial cells, immune cells, neurotransmitters, neuromodulators, and hormones (Herculano-Houzel, 2012: 1). Some glial cells such as astrocytes, microglia, and oligodendrocytes have a role in memory formation (Hertz & Chen, 2016: 1). To give an example, GABA neurotransmitters are responsible for pain relief (Yowtak, Wang, Kim, Lu, Chung, & Chung, 2013: 2469). The impact of immune T cells on stress responsiveness 1 exemplifies immune cells' implications to the human brain functions (Morimoto & Nakajima, 2019: 1). For instance, the neuromodulator histamine has a vital function in learning (Tasaka, 1994: 27). Also, androgen is linked with visuospatial ability (Ali, Begum, & Reza, 2018: 34). Further, the human

8**brain is influenced by** the **other** bodily **parts** such as **heart nerves** and **gut**

microbiome. For example, heart nerves affect attention and motivation (McCraty, Atkinson, Tomasino, & Bradley, 2009:16). Another example, a type of bacteria called Lactobacillus within the human gut microbiome increases the appetite for sugar (Leitão-Gonçalves, Carvalho-Santos, Fioreze, Anjos, & Baltazar,, 2017: 1; Appleton, 2018: 28). Through the efforts of researchers from various disciplines encapsulating the microbiologists, geneticists, biochemical engineers, chemists, medical doctors, and psychologists, a basic understanding of their functions at small scales is already known but an understanding of their functions at larger scales is still elusive. A new promising neuroscientific method, which is cutting the brain into a number of small

8**slices and** then **scanning them with a high resolution electron microscope**

is used recently (Zhu, Cizeron, Qiu, Benavides-Piccione, Skene, Fransèn, Komiyama,& Grant, 2018). The novelty of this approach comes from its surpassing challenges in scanning. In particular, a cubic millimeter of the mouse brain containing a hundred thousand neurons with a billion connections was cut into 25 thousand slices (Zhu et al., 2018: 781).

8**Five electron microscopes** scanned them **for five months collecting more than 100 million images**

. Additionally, the formation of a 3D model out of 100 million images of a single cubic millimeter of the mouse brain took three months. 2 Further, the data gathered from it took

8**up 2 million gigabytes of cloud storage. To** scan **the** human **brain**

, this whole endeavor has to be replicated a million times, since the human brain has around one million billion synapses. Consequently, complete data of the human brain would take thousands of years and two million petabytes. Surprisingly, these are just for mapping synapses. For a complete scanning of the human brain, each influencer of the human brain must be mapped out. More importantly, this would take millions of years and more data storage than that on the Earth. On top of that, all this effort provides a static mapping of the human brain instead of an active wiring of an agent. In order to reach an understanding of an active agent, the laws and rules governing the activity of the human brain at micro- and macro-level are necessary. As opposed to these neuroscientific approaches, there is a propitious computational approach called the predictive processing. Particularly, it suggests that it might not be necessary to scan everything in he human brain and its influencers. The human brain can be simplified into the probabilistic internal generative models that could match the human brain regarding its functions. To exemplify, a probabilistic generative model of the human brain can learn or false learn, remember or forget, imagine or dream, develop an action or remain inactive, and so forth. By simplifying the human brain into the generative models, it can be attained how the static mapping of the human brain leads to an active agent (Friston, 2010; Clark, 2013; Hohwy, 2013). However, similar to the human brain's development of myriad disorders, a generative model can develop a number of maladies. Specifically, if a probabilistic generative 3 model of the human brain is damaged in any of innumerable ways, then the agent may be in persistent pains, intermittent hallucinations, or endless delusions. From the faculties of the human brain to its disorders, maybe, the most peculiar thing about the human brain is pain. There are three reasons for that: (i) it is not a process that can be explained mechanistically because the human brain's pain answer is distributed across multiple brain areas (Corns, 2015: 3), (ii) it is not a proper scientific subject because it is indicated only by subjective report (Corns, 2018:1), (iii) the success rate of pain targeted treatments is not 100% implying that patients who suffered from pain will continue to suffer, and that pain management overrules pain treatment in the medical arena

(Main, Spanswick & Bartys, 2000). Yet, the computational approach to the human brain may promise innovative advancements particularly in understanding the emergences, maintenances, and treatment of experiences such as pain. Thus, in this thesis I investigate pathologically chronic pain and pain avoidance behavior within the predictive processing framework. Specifically, I ask

> 50**why physiologically** acute **pain outlives its** purposes **to** become **pathologically** chronic **pain**

, and why pathologically chronic pain is accompanied by pain avoidance behavior. I argue that by casting physiologically acute pain, pathologically chronic pain, and pain avoidance behavior as Bayesian probabilistic inference problems, different mechanisms having roles in the development, continuation, and treatment of distinct pains and behaviors emerged. 4 These mechanisms encapsulate perceptual inference, active inference, and active learning. I aim (i) to expand the predictive processing framework to pathologically chronic pain and pain avoidance behavior associated with the persistent pain by examining the explore-exploit dilemma, (ii) to make it functionally-explicable, (iii) to render it scientifically objectively comprehensible, and (iv) to pave the way for its treatment. In Chapter 1, I start by reviewing the pain theories that come to the front in the Philosophy of Mind, which are composed of evaluativism, imperativism, psycho-functionalism. I then discuss some of the worries that gained prominence in the literature. I also discuss whether or not these theories could tackle the main questions of the thesis. Chapter 2 shifts the conversation on pain to the review of the predictive processing

> 34**framework. In this chapter, I** discuss **the** conceptual background **of** the **framework**. That **is**

, I demonstrate how this framework roots from Bayesian Brain Hypothesis and the Predictive Coding Theory. I conclude the chapter by overviewing perceptual inference, active inference, and active learning. Throughout Chapter 3, I examine why physiologically acute pain outstays its functions to turn into pathologically chronic pain, and why pathologically chronic pain is associated by pain avoidance behavior. I claim that the main reason that distinct mechanisms take part in gaining information and producing actions regarding 5 physiological acute pain, pathologically chronic pain, and pain avoidance behavior is because of the influence of discrete levels of uncertainty on them. Through the explore-exploit dilemma, I draw the observation that

> 1**active inference and active learning** lead **to the emergence** and the preservation **of**

pain avoidance behavior and pathologically chronic pain, respectively. I also demonstrate how the perceptual inference explains the sensory and perceptual character of both physiologically acute pain and pathologically chronic pain. Before I conclude, I revolve around the implementations of the thesis in the scope of philosophy, neuroscience, and psychiatry. 6 CHAPTER I PAIN What is taken for granted regarding pain is that it is a complex, convergent, and multidimensional experience (Krahe, Springer, Weinman, & Fotopoulou, 2013). It encapsulates sensation, emotion, motivation, cognition, and social interaction. That is, it is modulated by bodily sensations (i.e., nociception), affect (i.e., attitude), evaluation (i.e., appraisal), action (i.e., volitional or involuntary behavior), and cognitive processes (e.g., attention, expectancy, or mood) and interpersonal interactions. It has phenomenal character, like other experiences with bodily sensational component, such as hunger, tickles, and itches. Its affective character is, mostly, unpleasant although there are cases of pleasant pain as well. When it is unpleasant, it motivates the body to take an action to mitigate it. If it is pleasant, then an action is taken by the body to protract it. Yet, little is known about the nature of pain and its biological markers in the human brain (Corns, 2016: 2950; Corns, 2018: 1). In the first instance, pain may be 7 physiological, pathological, or nociplastic (Woolf, 2010: 3742). Physiological pain is crucial for physiological, adaptive and protective system of the body. It detects the noxious incoming data and tissue damage, and signals for maintaining the integrity of the body. In the former case, this kind of pain is also called nociceptive pain because it relies on nociception (Figure 1A). Yet, if it is the latter, then it is also named inflammatory pain because it originates from inflammation on tissues due to damaging (Figure 1B). The adaptive and protective function of physiological pain calls for action such as relatively simpler behavior like withdrawal reflex or relatively more complex behavior like avoidance behavior. Consider an infant's encounter with the burn of the fire of a candle, the cut of the sharp edge of a knife, or the ice burn of the coldness of an ice cube. After the very first experience of the infant with the hot, sharp or cold objects, a withdrawal reflex may be demanded, whereas the following experiences may demand an avoidance behavior. Alternatively, an inflammation on the body as in the case of rheumatoid arthritis may call for an avoidance behavior. However, pathological pain is not protective, and it is maladaptive (Woolf, 2010: 3742). It is dysfunctional. It stems form malfunctioning of the nervous system because of a disease or a disorder damaging or irritating the nervous system. It is also mentioned as neuropathic pain (Figure 1C). In addition, nociplastic pain is not protective (Woolf, 2010: 3742). It is maladaptive and dysfunctional, as well (Figure 1D). Unlike pathological pain, it does not derive from a disease or a disorder. Consider a nociplastic pain due to fibromyalgia. 8 Additionally, a physiological pain may be acute or chronic (Figure 2A and 2B). If it is acute,

then it is short-lived—i.e., lasts less than six months, while if it is chronic, it persists—i.e., lasts more than six months (Grichnik & Ferrante, 1991:217). Further, acute pain is treatable, whereas chronic pain is irrespective of a current disease or disorder. Consider physiological acute tissue trauma pain resulted from stepping on a lego piece. Alternatively, consider physiologically chronic pain sprung from osteoarthritis. However, pathological pain may be acute or chronic. Consider pathological chronic pain brought about by stroke, spinal cord injury, multiple sclerosis, amputation, or diabetes. What's more, whether a pain is physiological, pathological, or nociplastic, what its matrices, biological processes, or neurological activation patterns are difficult to track down because when such neuroscientific methods are used, multiple areas of the human brain light up (Garcia-Larrea & Peyron, 2013: S30). That is, brain is not modular when it comes to pain. Apart from the nature of pain and its biological markers in the human brain, from whether or not pain is a natural kind to whether it is a mental experience, a bodily condition, or a representation, the controversies are numerous (Corns, 2018: 14). Further, if it is a representation, then the kind of representation is controversial. The neuroscientific approaches and the computational approach to the human brain, which aim to explain how an inactive wiring of the human brain generates an active agent, share an assumption. It is called strong representationalism according to which all mental states and processes are representational (Armstrong, 1961). In detail, it argues

> 43**that a mental state is** exclusively **determined by its**

intentional content (Dretske, 9 1995; Tye, 1995). In parallel, a representation is a mental object that bears an informative intentional content. For example, physiologically acute pain represents a physiological disturbance. Strong representationalism grounds these approaches to the human mind and has an advantage over its weaker version holding that the intentional content does not ground the mental state (Block, 1990) because it can explain all mental states and processes with qualitative character by reducing the phenomenal character to the intentional content. A qualitative character refers to "what it is like for one to be in that mental state" (Block, 1990). The bodily sensations such as hunger, tickles, itches, and pain have qualitative character. They pose a challenge for the weaker version of the representationalism. Particularly, what it is like to be in a physiologically acute pain experience for an agent cannot be accounted by the weak version of representationalism. However, the strong version of representationalism is not free of challenges. The opponents of the strong representationalism attack to pain's affective and motivational characters. Initially, all mental states and processes with affective character present a challenge for the strong version of representationalism. For instance, pain is affective in its nature. It is felt as either pleasant or unpleasant. That is, pain involves an attitude. Yet, the stronger version of representationalism cannot account for the affective character of pain. Additionally, pain motivates an agent to take an action. Yet, this motivational character of pain is not accounted by the strong 10 version of the representationalism. To explain the phenomenal, sensory, affective, and motivational characters of pain, evaluativism, imperativism, and psycho-functionalism emerge. 1.1 Evaluativism Regarding Pain The evaluative perceptualist theory regarding pain argues that pain is a perception. That is, pain has a modality-specific character called sensory character. This sensory character refers to the bodily condition. Evaluativism is, also, an intentionalist representationalist theory, which claims that pain represents a sort of bodily disturbance. This object of perception has an intentional content. It indicates that "something that is sensory—i.e., a kind of physiological disturbance, is the case". In this regard, it is an indicative content. In parallel, it needs to satisfy an accuracy condition. That is, it either affirms or denies that something is the case. Aside from its sensory character, evaluativism holds that unpleasantness or pleasantness of pain—i.e., its affective character, forms evaluative content of the representation (Bain, 2013). Consequently, according to evaluativists, there is a single representation composed of two distinct contents, which are called indicative content and affective content. Suppose that one drinks a glass of sour milk, and that therefore, she feels a specific type of pain in her stomach. Her pain represents that (i) a physiological disturbance in her stomach is the case, and (ii) this particular disturbance is unpleasant for her. 11 However, there are, mainly, three worries about evaluativism regarding pain. First, the messenger-shooting objection comes against the perceptualist aspect of evaluativism (Jacobson, 2013). Particularly, how evaluativism, like any perceptualist theory, explains the motivational character of pain appears to be problematic. It suggests that pain as a representation is equivalent to a messenger that informs the perceiver about the bodily disturbance. Given that pain's motivational character is what drives the perceiver to eliminate that pain when it is unpleasant for the perceiver, representing the physiological disturbance that motivates to get rid of the pain is equal to shooting the messenger. Yet, it is not clear that how shooting the messenger eliminates the bodily disturbance. For example, one receives an e-mail from her downstairs neighbor informing about the leakage from her ceiling that is unpleasant for her downstairs neighbor and her. In this setting, the e-mail functions as a representation with an informative indicative content and an affective content. Nevertheless, this e-mail does not give her a motivation to fix the leakage coming from her apartment. Additionally, deleting the e-mail does not mean that the leakage is fixed. Analogously, pain perception does not motivate its perceiver to eliminate the bodily disturbance. The second objection attacks evaluativism's representationalist aspect. It is called the problem of semantic focus (Aydede, 2009). Specifically, whether the semantic focus is on pain itself or on the semantic concepts that are related with the bodily disturbance is problematic. It proposes that when a bodily disturbance is perceived by a perceiver, the semantic concept PAIN is not applied to the bodily disturbance. The 12 semantic focus is already on the pain experience itself. For instance, in a scenario, in which one perceives a traffic light, vision is the modality, and the color information is the information that is specific to the visual modality. The object of this perception is the traffic light. At the

same time, this perception leads to the attachment of the semantic concepts such as RED, YELLOW, or GREEN, which become parts of the object of the perception. The last objection attacks evaluativism's intentionalist aspect. It is concerned with the accuracy condition of the representation's indicative content. That is, the necessary conditions that make the bodily disturbance an unpleasant pain accurate or inaccurate are still unclear (Corns, 2018: 6). Particularly, in evaluativism, a representation indicates that something is the case. In this respect, it has an indicative content that contains an accuracy condition. In other words, whether something is the case or not implies the accuracy condition of the representation. If a pain is a representation that accurately represents that the bodily disturbance is the case, then it is misrepresentation that inaccurately represents that the bodily disturbance is the case. It is possible that pain is a misrepresentation as well as that it is a representation. That is, whether all pains are misrepresentations or some pains are representation is not explicit in evaluativism. In the case of phantom pains of amputees, for example, a pain felt on an amputated limb is an inaccurate representation of a bodily disturbance. Hence, the phantom pain exemplifies a pain that is a misrepresentation. Yet, a pain felt on a healthy limb of the amputee due to accidentally hitting it on a wall may exemplify a pain as an accurate representation of the bodily disturbance. 13 In connection with the first and the third objections, I have an additional worry. If evaluativism is true, then how physiologically acute pain turns into pathologically chronic pain is problematic. In detail, pain is an overarching term that involves mainly physiologically acute pain and pathologically chronic pain. Pain caused by a broken leg bone is an example of a physiologically acute pain, while a neuropathic pain is an instance of pathologically chronic pain. Both are felt in certain areas of the human body with varying degrees of intensity. The acute and chronic pain perception differs from each other with respect to their motivating force for an action and their accuracies regarding their felt places and intensities. In an evaluativist setting, they appear to be problematic in some ways. First, if evaluativism is true, then physiologically acute pain is purposeful—i.e., it has a sort of utility for the perceiver such as warning the human body from of injury and motivating her to take an action. Second,

> 13**if evaluativism is true, then** physiologically acute **pain is** an accurate **representation**

of either internally- or externally-caused sensation of the bodily disturbance. At the same time,

> 13**if evaluativism is true, then** pathologically chronic **pain is**

, also, purposeful. Supplementally,

> 13**if evaluativism is true, then** pathologically chronic **pain is** an accurate **representation**

because it accurately represents a sensation of the bodily disturbance. However, it is not the case that pathologically chronic pain is purposeful and an accurate representation of a bodily disturbance. Therefore, evaluativism does not account for what results in a misrepresentation that was once a representation and the lack of motivation for an action-taking that was once there. 14 1.2 Imperativism Regarding Pain The imperative representational theory of pain holds that pain represents an imperative. This representation—i.e., the command, has an intentional content. In parallel, this intentional content forms the command's imperative content. Different from evaluativism, it represents that "something is to be done" in imperativism (Klein, 2015). In this respect, it comprises information about an action performed by the agent. The action may be either to stop doing something or to protect the human body. Additionally, as opposed to the accuracy condition of the indicative content in evaluativism, the imperative content has a satisfaction condition. That is, it either satisfies or dissatisfies that something is to be done. In parallel, pain motivates doing or acting on something directly through its imperative content (Hall, 2008: 530). However, some pains may represent an unsatisfiable or an already satisfied command. Consider headaches, neuropathic pains, and phantom pains as examples to such pains (Martinez, 2015). There are mainly three arguments against imperativism with regard to pain. The first argument against imperativism with regard to pain is concerned with the imperative content of pain. In particular, it argues that there are some pains that do not motivate their agents to take actions, and they are problematic for imperativism. Consider that morphine pain and pain after lobotomy do not result in action (Grahek, 2007). The second argument against imperativism is about the pain's imperative content, which is called the problem of authority (Bain, 2011: 180). Precisely, it contends that a command does not motivate an agent to execute an action concerning pain, and there 15 is a problem of authority in imperativism. What motivates a system or an agent to take an action is the reason, which gives the authority to the system or the agent herself. The third argument against imperativism concerning pain is about the sensory and affective characters of pain (Corns, 2018: 9). Clearly, it asserts that imperativism concerning pain does not account the pain's sensory and affective characters, although it reflects the motivational aspect of pain. In addition to these three worries about imperativism regarding pain, I have an additional worry. How physiologically acute pain turns into pathologically chronic pain is problematic for imperativism similar to that it is the case for evaluativism. To be specific, what changes the satisfaction command of an acute pain to the satisfaction command of a chronic pain is unclear in

imperativism. That is, what determines the move from being satisfiable to being unsatisfiable is elusive. In other words, the condition for an unsatisfiable pain is lacking in imperativism. For instance, if evaluativism is true, then a phantom pain necessarily remains unsatisfiable. However, this is not the case in that Ramachandran's mirror-box approach to phantom pain satisfies such pains (Ramachandran, 1998). 1.3 Psycho-functionalism Regarding Pain Contrary to evaluativism and imperativism, psycho-functionalism is a theory against the strong representationalism. It holds that pain represents a kind of bodily disturbance as its sensory intentional indicative content. Unlike the evaluativists and the imperativists, however, the psycho-functionalists reject the argument that the 16 affective character of pain has an intentional indicative content because because it has a qualitative character and a functional character irrespective of the accuracy condition of a representation's content. That is, regardless of whether there is a representation or misrepresentation, it functions in the development of the affective-

41**motivational character of pain**. Instead, **the** affective **and motivational** characters **of**

pain arise from the processing of the representation's indicative content. This is called m-processing occurring at sub- personal level. The m-processing of a sensory information leads to either attraction or aversion. This forms phen-desiring, which refers to the formation of desires regarding either pleasant or unpleasant content. In addition, m-processing results in phen- beliving. That is, it has a role in the formation of beliefs concerning the sensory information. Further, m-processing which is composed of phen-desiring and phen- beliving shapes reason for action. If there weren't a reason for an action, then a command would not motivate an agent to take an action. Also, if there is a reason for an action, there is no need for a command. Therefore, m-processing gives rise to actions, desires, and beliefs without an affective intentional content, as in evaluativism, and without a command, as in imperativism. Against psycho-functionalism, there is one major worry. It is about its sub-personal aspect. To be specific, it argues that sub-personal level m-processing does not elucidate the normative reasons for action (Bain, 2013). In order to explain the normative motivations to act, personal level processing is necessary. Additionally, I 17 have a further worry about psycho-functionalism. Similar to the case for both evaluativism and imperativism, the way, in which a physiologically acute pain becomes a pathologically chronic pain, creates a problem for psycho-functionalism. Namely, if psycho-functionalism is true, then all agents with pathologically chronic pains must have the same sub-personal and functional processing. Otherwise, an agent with a slight individual difference in the sub-personal and functional processing does not count as having pathologically chronic pain. It is, yet, the case that pathologically chronic pain manifests individual differences from one agent to another although these individual differences are not accounted scientifically at the sub-personal level. Therefore, psycho-functionalism cannot explain the individual differences of the agents with pathologically chronic pain. 18 CHAPTER II THE PREDICTIVE PROCESSING FRAMEWORK From the conversation on pain, I move the dialogue toward the conceptual background of the predictive processing framework before examining pathologically chronic pain and pain avoidance behavior. Particularly, this framework roots from Bayesian Brain Hypothesis and the predictive coding theory. Nevertheless, the fame of the predictive processing framework comes from perceptual inference, active inference, and active learning.

5**Thus, I start by providing an overview of**

Bayesian Brain Hypothesis and the predictive coding theory. Then, I dwell into perceptual inference, active inference, and active learning before inquiring why physiologically acute pain outlives its protective and adaptive functions to turn into pathologically chronic pain and why pain avoidance behavior and pathologically chronic pain are associated. 2.1 Bayesian Brain Hypothesis One of the approaches to cognition is Bayesian Brain Hypothesis. It is an overarching hypothesis composed of several different models to account for divergent domains 19 and distinct levels of cognition. Importantly, it is the underlying hypothesis of the

22**predictive processing framework. The** main tenet **of this**

hypothesis is that

33**brain is a Bayesian inference machine (Friston, 2010). The**

underlying principle of this view is that the brain has

7**only indirect access to the** bodily **internal** states **and** the environmental **external**

states. Consequently, it must infer the sources or causes of these states. That is, brain generates probabilistic internal inferences following Bayes' rule. Then, what is a Bayesian probabilistic inference? A

Bayesian inference, prediction, belief or information is a statistical probability distribution over an unknown source or cause of a state (Friston, 2010). In that sense, Bayesian beliefs are different than the explicit propositional beliefs. Particularly, Bayes' rule or Bayes' theorem is a means of computing a probability of predictive information when other certain probabilities of predictive information are known. Its formula is

> 27**as follows. P(A|B) = P(A) P(B|A) / P(B) This**

formula tells us that suppose there are two separate predictive information call 'A' and 'B'. What we want to find

> 23**is P(A|B)** when **P(A), P(B)**, and **P**(B|**A**) are known. **P**(A|**B) tells us**

> 10**how often** 'A' **happens given that** 'B' **happens. P(A)** tells us **how likely 'A' is on its own. P**(B) tells us **how likely 'B' is on its own**, and **P(B**|A) tells **us**

20

> 10**how often** 'B' **happens given that** 'A' **happens**. In other words, **P(A|B**

), which is a probabilistic inference reflects the integration of P(A), P(B), and P(B|A), which are

> 14**predictive information, in an approximately Bayesian optimal way**. What can be **the** sources or **the** causes **of** predictive **information**

? Namely, the sources of these predictive information can be either the prior predictions— the priors, that are encoded

> 42**in the** generative **model** or **the** likelihoods **of the current potentially**

multi- sensory noisy information. If a belief is prior to an observation of a sensory input, then it is called a prior belief. Additionally, the likelihood is the sensory evidence (Figure 3). What does the Bayesian optimal integration mean? It is an optimal integration because it is based on their precision or uncertainty weights (Figure 3). That is, the predictive information that has more precision influences the integration more. In parallel, the more uncertain predictive information is, the less the influence is on integration (Figure 4). Nevertheless, optimality does not refer to accuracy (Tabor & Burr, 2019: 58). Thus, there may be a decoupling between a likelihood about incoming sensory information and a prior. Therefore, Bayesian optimal integration can result in a detachment from veridical sensory evidence. What is got after the Bayesian optimal integration, then? If a prior belief is Bayesian optimally integrated to either another prior belief or likelihood after observation of a new sensory data, then a new belief called a posterior belief is formed (Figure 4). Yet, 21 it is essential to note here what governs the Bayesian optimal integration. That is, the likelihood and the prior do not necessarily match. The mismatch between them governs the posterior formation through the Bayesian optimal integration. In other words, the Bayesian optimal integration is centered on the comparison and adjustment of the prior belief and the sensory input. However, why is the Bayesian optimal integration necessary, and why is it maintained over time? It is required for the formation of a belief that will be necessitated for the access to the source of a state. It is maintained in order to increase the degree of precision that is associated with a belief. That is, a belief is attached with a certain degree of precision. In other words, precision implies certainty that is associated with a belief. The precision of a belief, which is based on a sensory input, is tested against the

> 48**precision of the** sensory **data**. Further, **the precision of the**

sensation provides either evidence in favor of or evidence against the prior belief. What is the evidence against a prior belief in light of sensory data? It is the precision of

> 35**prediction error**, which **is calculated** via **the difference between the** precision of **the**

sensory data and the precision of the prior (Figure 3). That is, the precision of the prediction error provides how much evidence is given. In this respect, what governs the Bayesian optimal integration is the prediction

error. Does this imply that the Bayesian optimal integration is biased?. Based on the relative

> 21**precision of the sensory input and** that **of** the **prior**

—i.e, based on the precision of the 22 prediction error, the posterior belief biases toward either of them. Suppose that the posterior belief is biased towards

> 9**sensory evidence** by **either increasing the precision of sensory input** and/**or failing to attenuate it or decreasing the precision of the prior belief**

(Figure 4-5). What is exactly the function of the prediction error? It is signaling learning, which occurs through the Bayesian optimal integration. How much learning is occurred is called the learning rate. It is calculated by the ratio of the

> 21**precision of the prediction error** and **the** precision **of** the **prior**

. Consider that the prior is constant, the learning rate relies on the precision of the sensory input. In this sense, the learning is open to change and the learning rate is variable. In parallel, a system can adapt to dynamically altering uncertain environment. However, how can the learning rate be increased allowing a system to adapt to its environment? It is ensured though a single imperative, which is the minimization of prediction error.

> 45**It is important to note that, the** prediction error **minimization**

should occur over the long-term average. To exemplify, if the precision of prediction error is too large, then the prediction error minimization will be excessive and the learning rate will be vast. Through prediction error minimization, a system adapts to its ever- changing and uncertain environment. What, more importantly, can a prediction error signal other than learning? It is false learning. That is, the predictive error minimization leads to maladaptation to an 23 environment. False learning or maladaptation to an environment is probable.

> 18**If the precision of the** sensory input **is overestimated or the precision of the prior is underestimated**, then **the**

precision of the prediction error will be huge. This situation yields that the posterior moves towards the sensory mean and away from prior mean. Consequently, this results in false belief or false inference. This culminates in a maladaptation of the system or the agent to the body or the environment. 2.2 The Predictive Coding Theory The predictive coding or Bayesian coding hypothesis is the first steps of the

> 22**predictive processing framework**. It depicts **that beliefs are** encoded in **the** form **of**

probabilitydensity distributions (Friston, 2010; Clark, 2013). Having said that probability density distributions encode uncertainty, encoding beliefs implies that the neural systems of biologically possible models take uncertainty into account fundamentally. Therefore, this hypothesis postulates that brain's learning can be cast in terms of statistics, in which uncertainty is transmitted within the neural networks (Rao & Ballard, 1999: 79). It suggests that, through this way, the neural networks optimize their connectivity and the dynamics among them in order

> 32**to maximize the evidence for its** generative **model of the**

environment (Hohwy, 2016: 259). 2.3 The Predictive Processing Framework The predictive processing framework casts Bayesian probabilistic inference pertaining to the prediction error minimization over the long-term average (Hohwy, 2013; Clark, 2013). That is, an internal generative model of a system or an agent 24 produces innumerable beliefs that are directed to capture the incoming sensory information. Then, what is a generative model? A hierarchical probabilistic internal generative model is

> 7**used to generate** an **expected** consequence **that may arise from hidden (latent)** state **of the** body or the **environment, and**, even, **in** the **absence of** the **external**

stimulation

(Figure 6). It is

7**shaped over time to reflect** a precise representation **of**

the body and the environment. The prior beliefs are formed by the relatively higher mental states and carry weight with the relatively lower mental states, and that therefore, they are called top-down beliefs (Tabor & Burr, 2019: 55). The sensory data is created by the relatively lower mental states and carry weight with the relatively higher mental states. In parallel, they are also named bottom-up beliefs (Tabor & Burr, 2019: 55). In this regard, there is a hierarchy of beliefs within the model of the system. There are also bidirectional connections among them. That is, there are multi-level connections among beliefs. The internal generative model chooses the top-down belief that best matches with the sensory input thereby the prediction

51**error between the** prior belief **and** the **sensory data is**

minimized. After the countless trials of matching of the priors with the inputs, the internal generative model of the system promises the prediction error minimization over the long-term average. The reason lurking behind the process of prediction error minimization over the long- term average within the predictive processing framework is the hierarchical internal generative model's encoding of the probability distributions of the beliefs with uncertainty. The uncertainty encoded in the generative model is tackled with the precision-weighting process, where a belief associated with the highest precision is 25 weighted against the others. By the transmission of the difference between the belief with the highest precision and the actual sensory input

20**in the** form **of prediction error, the prediction error**

minimization occurs. The repetition of this process results in the prediction error minimization over the long-term average, in which the prediction error gets closer and closer to zero and the match gets closer and closer to exact match. 2.3.1 Perceptual Inference

36**Perception is a process of probabilistic** knowledge-driven **inference in the**

predictive processing framework (Clark, 2013: 2). It

29**arises as a result of** the **successful prediction-error minimization**

. To infer the source or the cause of an incoming sensory information or to perceive is perceptual inference (Clark, 2013: 6; Hohwy, 2013: 14). It refers to a mechanism that aims to meet the encoded sensory data with a prior belief of the hierarchical internal generative model of a system or an agent. That is, the prior is tested against the actual sensory input. An internal generative model encodes beliefs about the body and the environment as multiple top-down probability distributions

7**with differing degrees of** uncertainty. These **reflect a range of candidate** beliefs **about the** potential causes **of the** sensory state of **the** body or the **world**. Therefore, **the**

prior belief of the generative model may be from various spatial and temporal levels. 26 However, it is not exact issue of matching the prior directly with the sensory input. It is directed

16**to minimize the prediction error** that arises from **the** difference **between the** sensory information **and the**

prior over the long-term average (Clark, 2013: 7). Given that, it aims to use the prediction error

38**as a learning signal to** revise **the** system's **internal** generative **model**

of its body and environment, the perceptual prior beliefs refer to what the generative model has learned from

its previous encounters with the source of the incoming sensory data (Clark, 2013: 7). When the prior beliefs are tested against the actual incoming sensory information, the evidence for the internal generative model is maximized for the accurate and precise beliefs. Further, the process of matching the prior with the sensory input involves computing various probability distributions of the sensory data (Clark, 2013: 7). The reason is that an inference may

> 15**be consistent with many** distinct **sets of causes**. They can be **distinguished only by their relative**

probabilities of occurrence. 2.3.2 Active Inference Action, within the predictive processing framework, is an inferential process (Clark, 2013: 6). The inference of an action by a system or an agent results in either an inferred outcome or predicted information through the action. In this regard, the inferred action is either exploratory or exploitative. That is, the system selects either an exploratory or exploitative optimal action policy to achieve what is estimated. The policy means a sequence of states leading to the concrete action or behavior. Under the selected policy, prediction errors may be induced because of the mismatch between what is estimated and what is the current case. The system selectively 27 samples inputs to minimize the prediction errors under that action policy. To selectively sample, the system may alter its actions under that policy, thereby the sampled input may better reflect the predicted outcome or information. In parallel, there are two kinds of mechanisms described under

> 37**active inference (Friston, FitzGerald, Rigoli, Schwartenbeck, O'Doherty**, & Pezzulo, **2016**

: 864; Gadsby & Hohwy, 2019: 3). A particular mechanism of active inference is for utility. It is for reaping an outcome or reward. The other mechanism of active inference is for epistemic value. It is for reducing uncertainty about a system's internal generative model of its body or environment. Importantly, under active inference process, the systems cover the reduction of uncertainty within its model by means of fixing the model and changing its actions. 2.3.3 Active Learning An active system or agent minimizes prediction errors through either by carrying out actions to sample input that better captures what is inferred or by updating the parameters of the system's internal generative model to produce predictions that better reflect data (Friston et al., 2016: 864; Tabor & Burr, 2019: 55). The former alternative is introduced under active inference process. The latter is called active learning. The inference of an action policy under active learning is for mitigating uncertainty about the system's model. Instead of fixing the model and changing its actions, as

> 19**it is** 28 **the** case **for active inference, the model**

itself is updated in active learning. What updates the model is information in active learning process. In that sense, the inferred action policy is exploratory. Specifically, Bayesian optimal integration of the incoming information and the prior beliefs occurs over time to minimize the future prediction errors (Tabor & Burr, 2019: 56-7). That is, an active learner actively infers with increasing precision in future encounters (Clark, 2013: 10). 29 CHAPTER III WHY DOES PHYSIOLOGICALLY ACUTE PAIN OUTLAST ITS PURPOSES TO TRANSFORM INTO PATHOLOGICALLY CHRONIC PAIN AND WHY IS PATHOLOGICALLY CHRONIC PAIN ACCOMPANIED BY PAIN AVOIDANCE BEHAVIOR? Why physiologically acute pain outstays its functions to become pathologically chronic pain, and why pathologically chronic pain is accompanied by pain avoidance behavior remained elusive within the predictive processing framework. Essentially, in order to answer to these questions, I cast pathologically chronic pain and pain avoidance behavior as Bayesian probabilistic inference problems. Given that pain is a complex, convergent, and multidimensional experience, a Bayesian probabilistic model of pathologically chronic pain involves sensory, perceptual, affective, and motivational aspects. To date, the most researched feature of pathologically chronic pain within the predictive processing framework is established on perceptual inference. Following that, initially, I demonstrate what the perceptual inference account refers to regarding pathologically chronic pain. Up-to-date research holds that a complete understanding of pathologically chronic pain necessitates an explanation 30 of its motivational character, as well. However, when casting pathologically chronic pain and pain aversive behavior as Bayesian probabilistic inference problems, their motivational aspects call upon the explore-exploit dilemma and the

> 1**emergence of active inference and active learning**

. In parallel, I call attention to the different levels of uncertainty and their influence on the

> 1**emergence of active inference and active learning**

. Additionally, I show that different mechanisms are at work in gaining information and producing actions regarding pathologically chronic pain and pain avoidance behavior. Finally, I will propose that

1**active inference and active learning** lead **to the emergence of**

pain avoidance behavior and pathologically chronic pain, respectively. Therefore, section 1 describes the influence of perceptual inference over pain. Section 2 lays

15**out the key elements of the** explore-exploit dilemma. **Section 3**

elaborates the implications of this dilemma on the unfolding of pathologically chronic pain and pain aversive behavior that accompanies pathologically chronic pain. 3.1 The Perceptual Inference Account of Pathologically Chronic Pain Briefly, perceptual inference is a mechanism that functions in gaining information about the state that causes pain perception. What is inferred when pain is cast in terms of the perceptual inference is the cause of nociception. Perceptual inference is governed by the minimization of the mismatch between the encoded relative precisions of the incoming sensory data and the prior belief in the predictive processing framework. In parallel, this principle applies to pain encapsulating physiological, pathological, and nociplastic pain resulting in nociceptive prediction error minimization. 31 The research on the sensory aspect of pain, particularly, nociception goes back a long way. Pain perceptions generally involve nociceptive aspect, although it is not necessary for all pains. For example, some patients with pathological pains arisen from spinal cord injury, or some patients with nociplastic pains resulted from fibromyalgia do not have nociception. Yet, in the case of physiological pain, there is generally nociception. One exception is congenital insensitivity to pain, which causes the lacks of nociceptors and, in parallel, the encoding of nociceptive input to the model of a system or an agent (Woolf, 2010: 3742). What governs the physiological nociception is the minimization of the mismatch between the relative precisions of the physiological noxious input and the prior belief in the generative model of a system or an agent. As to pathological pain, there is two directions to take. First, if there is not a nociceptive aspect of a particular pathological pain, then the perceptual inference account is insufficient to explain the pathological pain. Second, if there is a nociceptive character of a certain pathological pain, then the same principle—i.e., the

31**prediction error minimization**, applies. **However, this is the** tricky part. **The** reason is **that**

the perceptual inference mechanism points to the presence of an underlying deficit in precision optimization within pathological pain. Specifically, the prediction error is a function of the relative uncertainties of beliefs resulted from the actual nociceptive cause and the prior encounters with the nociceptive source. It should be minimized over the long-term average. It occurs through Bayesian optimal 32 integration. That is, Bayesian optimal integration implies the nociceptive prediction error minimization. However, it is biased. It allows that the posterior nociceptive belief, which is formed via integration of the sensory information and the prior belief, biases toward either of them. It may bias towards the nociceptive evidence by either

9**increasing the precision of** nociceptive information and/**or failing to attenuate it or decreasing the precision of the prior**

beliefs. Bayesian optimal integration indicates nociceptive learning. In other words, the nociceptive prediction error minimization means learning. If it occurs, then a system or an agent can adapt to the dynamically altering uncertain body and environment. However, false nociceptive learning may occur too. Having said that Bayesian optimal integration is biased, the precision of a nociceptive input may be overestimated and/or the precision of a prior may be underestimated or vice versa. This may result in the nociceptive posterior moves towards the sensory mean and away from prior mean. Through this, the predictive error minimization leads to maladaptation to the body or the environment or false learning, false belief, or false inference. That is to say that the nociceptive posterior belief may spend time deviating from the optimal nociceptive inference. This inference will manifest as more or less transitory false nociceptive inference or entrenched false nociceptive inference. As a result of the deviation from the optimal inference, it may fail to correct itself over time. This leads to a cascading and increasingly ensconced malfunctions. This refers to the pathological condition. As a result, this provides a ground for addressing how pathological pain perception is formed and maintained against counter perceptual evidencies. Given that the deviation from the optimal nociceptive inference requires time, the pathological pain 33 is maintained over time. The reason is that the reliance relatively more on nociceptive information leads to sampling and solving the uncertainties on the body and the environment more and for longer time. The deviation may entail time less than six months. In such a case, it may be referred as pathologically acute pain. However, if it endures more than six months or even a life time, then this may make it pathological chronic pain. Analogous to pathologically chronic pain perception, many psychopathological disorders are associated with inappropriate beliefs about precisions of the prior beliefs and sensory information. That is, they are linked with entrenched false inferences. To exemplify, autism spectrum disorder has been related with higher prior expectation for the sensory precision (

25**Van de Cruys, Evers, Van der Hallen, Van Eylen, Boets, de-Wit, & Wagemans, 2014**

). Particularly, a patient with autism spectrum disorder appeals relatively more to the senses than the priors with in the agent's hierarchical internal generative model's parameters (Hohwy, 2013: 161) Hallucinations in schizophrenia have been connected with higher prior expectations for the variations of the sensory input (Sterzer, Adams, Fletcher, Frith, Lawrie, Muckli, Petrovic, Uhlhaas, Voss, & Corlett, 2018). Delusions have been concomitant with false inference that is resulted from the reduction of the sensory precision in comparison with the prior precision (Adams, Brown, & Friston, 2014). Specifically, there is a heightened and continuous expectation for uncertain sensory data and increased and persistent reliance on the prior beliefs in both hallucinations in schizophrenia and delusions (Hohwy, 2013: 158). It is hypothesized that heightened chronic pain 34 expectation gives rise to heightened chronic pain perception (Hechler, Endres, & Thorwart, 2016). 3.2 Is Action Required for a Full-Fledged Account of Pathologically Chronic Pain? If a system or an agent has settled on a posterior perceptual or nociceptive inference resulted in pathologically chronic pain, then why action should have a role in the system or the agent with pathologically chronic pain is a further inquiry. An answer may come from two different trajectories. If a pathologically chronic pain has a nociceptive aspect, then two supportive arguments in favor of action may be given. First, without action none of the beliefs of an agent can be favored strongly (Hohwy, 2013: 79). That is, action increases the precision and the accuracy of an inference encoded as a probability distribution. For example, suppose that one has happened to step on a lego piece in the middle of the night when she was trying to figure out the location of the light switch on the wall. The perceptual inference accounts for the noxious nociception caused by stepping on the Lego piece. She acts to minimize the following mismatch between the incoming sensory information—i.e., that there is something on the floor that may cause a damage on the body, and the prior inference—i.e., that the body integrity is intact. Many things can cause the exactly same inference. What causes this particular perception, which is a Lego piece, can be understood only by pulling her leg up, and turning her head down and gazing at the stuck piece on her foot. 35 Second, action is relatively more efficient than relying just on the perceptual inference (Hohwy, 2013: 80). In other words, to stay put for perceptions requires time, and it hereby is inefficient way to favor strongly an inference. For instance, one decided not take an action to turn the lights on and remained curious about what was the cause of noxious nociception perceived a couple of minutes ago in the middle of the midnight. Instead of carrying out an action to switch on the lights, she will wait the sunrise, thereby the sun light will fill the room and light the cause of nociception. This may take for hours. In contrast, switching on the lights takes just a couple of seconds. Therefore, active inference is relatively more efficient than the perceptual inference given a particular situation. However, the second trajectory comes from where there is no nociceptive information. That is, if there is not a nociceptive aspect of a pathologically chronic pain (along with nociplastic pain), then what makes the pain pathological and chronic (or nociplastic) necessitates an account of action. Hence, the perceptual inference account of pathologically chronic pain is insufficient for its complete understanding. It fails to account for its motivational aspect. What's more, the perceptual inference account of pain fails to account for the accompanying pain avoidance behavior. For instance, suppose one has a leg fracture due to falling on ice that may heal in three months. According to the perceptual inference, she will perceive a physiologically acute pain due to the fracture over this period of time. Especially, suppose that she perceives more pain when there is 36 pressure on the location of the fracture. Thus, she avoids leaning on her broken leg's side while sleeping to avert the perception of the physiologically acute pain. Suppose, further, that her perceptual inference deviated from its optimal precision and resulted in an entrenched pathologically chronic pain. Having said, she avoids to lean on her broken leg's side while sleeping to avert the perception of the pathologically chronic pain. Therefore, irrespective of whether this is a physiologically acute pain or a pathologically chronic pain, an account of action regarding pain is necessary. 3.3 The Explore-Exploit Dilemma: The Gap in the Pain Literature When pathologically chronic pain, which has a motivational aspect, and pain avoidance behavior are cast in terms of Bayesian probabilistic inference problems, they call for a deep scrutiny of action within the predictive processing framework. Bayesian probabilistic internal generative models are characterized by exploitative action or exploratory action strategies (Figure 7). In parallel, active inference and active learning lead to attenuation or uplift of the exploration and exploitation strategies as functions of prediction error minimization over the long-term average (Hohwy, 2013: 71; Marković , Goschke, &Kiebel, 2020: 3). Particularly, the equilibrium between exploration and exploitation is governed by the minimization of uncertainty by means of active inference and active learning (Seymour & Mancini, 2020: 5). However, balancing exploration and exploitation brings along the explore- exploit dilemma. It refers to knowing when to switch to exploitation of learned information, and to pause exploring for new information about an ever-changing and uncertain environment, and vice versa (Marković et al., 2020: 2). That is, if a certain 37 action yields prosperous surprise minimization, then how long the action should be prolonged culminates in the dilemma. Specifically, if the action perpetuated, then the system or agent would never know if the action is necessitated indefinitely within the environment, or if the cause of the action has otherwise ceased (Schwartenbeck, Passecker, Hauser, FitzGerald, Kronbichler & Friston, 2019: 1). Exploitative actions are outcome-driven actions (Friston et al., 2016: 863). That is, they are the best actions that result in the best outcomes based on the present beliefs about the environment (Schwartenbeck et al., 2019: 1). In this respect, they are pragmatic and susceptible to risks (Seymour & Mancini, 2020: 5). Contrarily, exploratory actions are information-driven actions (Friston et al., 2016: 863). In other words, they are the actions that yield information about whether

14**there are** any **better** action **whose outcome is partially or fully unknown**

at present (Schwartenbeck et al., 2019: 1). In this sense, exploratory actions are epistemic and susceptible to ambiguity (Friston et al., 2016: 863). There are two kinds of exploratory strategies: goal-directed and random exploration (Friston et al., 2016: 863). Goal-directed or directed exploration is motivated by uncertainty within a system's model of the environment based on either the uncertain mapping from a state to an outcome or an uncertain state (Schwartenbeck et al., 2019: 2). This entails that the system samples information that is held with the highest uncertainty (Schwartenbeck et al., 2019: 2). In addition to that, the goal-directed 38 exploration adds cost, noise, or bonus to policy that is arbitrarily chosen due to the highest uncertainty (Kakade & Dayan, 2002: 554). Here

1**it is important to note that** there are two **types of**

uncertainty or surprise, which are unexpected uncertainty and expected uncertainty (Schwartenbeck et al., 2019: 2). Unexpected uncertainty refers to ambiguity, whilst expected uncertainty refers to risk (Figure 8). In parallel, an exploitative policy is sensitive to expected uncertainty, whereas an exploratory policy is sensitive to unexpected uncertainty. Essentially, for a system, it is necessary to tackle with an ambiguity before tackling with a risk of a policy (Schwartenbeck et al., 2019: 2). There are, also, two types of goal-directed exploration: the hidden state exploration (Figure 7B), and the model parameter exploration (Figure 7C). Goal-directed ambiguity reduction relies on the mapping between the hidden state and the observation. That is, a system must infer both the action policy and the current hidden state that causes the observation. If the mapping from underlying a hidden state to an outcome is unambiguous, then the system can navigate to the outcome. This implies that the system can actively sample until it achieves the outcome, which has unambiguous mapping to the hidden state (Figure 9). In other words, the hidden state exploration can occur through active inference (Schwartenbeck et al., 2019: 2). Active inference ensures the hidden state exploration by driving a system to actively look for already learned or known salient 39 outcome that provides an inference of the hidden state unambiguously (Schwartenbeck et al., 2019: 5; Tabor & Burr, 2019: 56). For example, suppose that one flips a certain coin and always observes heads. Additionally, one has learned previously that a loaded coin always shows heads, and a normal coin shows a mixture of heads and tails when it is flipped a number of times. Thus, the mapping from the hidden state to the observation is unambiguous. In parallel, suppose that her inference is to observe heads if she flips it one more time. The hidden state that causes this observation and inference may result from that this certain coin is a loaded one. Yet, the hidden state can be just luck, as well. In this scenario her expected uncertainty is based on that this certain coin is loaded. Contrarily, her unexpected uncertainty is based on the idea that the observation of heads is due to mere luck. Her inference will be that if they rely on luck, then the coin will show tails at least one time; and if they are because of coin's being loaded, then the coin will show heads all the time. In order to minimize the unexpected uncertainty, her inferred policy will be to flip the coin multiple times. Suppose that she observes heads irrespective of the number of times flipping the coin. Thus, she infers that the coin is actually a loaded coin. However, if a system is ignorant about the mapping of its model, then the system acts in order to learn its model's previously unexplored contingencies. That is , if in a goal-directed exploration, a system needs to reduce not only the uncertainty

1**about the current hidden state**, but also **the** uncertainty of **the**

mapping between the hidden state and an outcome along with inferring the best action policy that is uncertain at present to achieve the uncertainty reduction, then it is model parameter exploration (Figure 40 9). It occurs through active learning (Schwartenbeck et al., 2019: 5). Active learning assures the model parameter exploration by compelling a system to actively try out

1**novel combinations of** the **hidden states and outcomes** in order **to** actively **learn about the** mappings, **in which** the **outcomes are**

guaranteed (Schwartenbeck et al, 2019: 7; Tabor & Burr, 2019: 55). To exemplify, suppose one wants to make soft chocolate chip cookies. Yet, suppose that she has a knowledge gap concerning the recipe of soft chocolate chip cookies. Particularly, she is uncertain about whether adding too much or not enough flour makes a chocolate chip cookie soft. Additionally, suppose that she is not certain concerning whether over-beating or under-beating the eggs produces soft chocolate chip cookies. Moreover, suppose that she has not learned whether she should melt the butter or she should not melt the butter for soft chocolate chip cookies. In this setting, her mapping from the hidden state, which is the recipe, to the observation, which is the softness of the chocolate chip cookies, is ambiguous. That is, these contingencies are associated with the highest uncertainties. To fill her knowledge gap— to learn and minimize the uncertainties, her inferred policy will be to actively try out novel combinations of the amounts of flour, egg-beating, and butter-melting. Additionally, for active learning to occur there must be

1**stable regularities or rules in** an environment **that can be learned**

(Figure 9). That is, active learning refers to being able

1**to carry information from one trial to the next. This is** provided **by the**

regularities or rules in an environment. Further, active learning occurs over time. In that sense, it is a slow way to reduce uncertainty. Contrarily,

1**active inference can** 41 **often be a faster way of reducing uncertainty**

(Schwartenbeck et al., 2019: 25). In the cases where active learning is broken and it is possible to calculate uncertainty, active inference can reduce uncertainty instead of active learning. In contrast to goal-directed exploration, random or undirected exploration (Figure 7A) is directed to randomly sampling information regarding the altering and uncertain environment while diverging from the best action already learned given the current beliefs (Schwartenbeck et al., 2019: 1). This entails that a randomly exploratory action is not informed by a system's uncertainty regarding a hidden state or its mapping (Schwartenbeck et al., 2019: 8). Importantly, random exploration can allow a divergence from the currently best action policy whose outcome is fully and certainly known. It also occurs through active inference.

1**This implies that such** an action **will not decrease uncertainty per se but may cause accidental belief updating** or learning **due to random or stochastic selection of different policies**. In **this**

regard,

1**random exploration may** have **an adaptive function in the absence of goal-directed exploratory**

actions that may be a result of a system's inefficacy to calculate uncertainties—i.e., active inference and/or learning is broken (Schwartenbeck et al., 2019: 10, 25). Therefore, goal-directed exploration can refer to either exploring the hidden state that causes the outcome or exploring the parameterization of the system's model. Concurrently, gaining information and uncertainty minimization can be achieved by either

1**active inference** or **active learning. In** other words, **the** exploration **of the**

hidden 42 state is called active inference, whereas the exploration of the model parameterization is called active learning. Furthermore,

47**in the** lack **of goal-directed** exploration, **random exploration may**

result in adaptive learning. Importantly, inferences made through hidden state exploration by active inference and through model parameter exploration by active learning can either support or oppose each other (Schwartenbeck, 2019: 5). If there are regularities and/or rules within a system's environment that are stable enough in order to be learned through time by a system, then the hidden state exploration can be cast in terms of active learning. In this setting, the prediction made through hidden state and model parameter exploration boost each other (Schwartenbeck et al., 2019: 24). However, if the context changes randomly, then the hidden state exploration is cast in terms of active inference and may contradict with an inference made by active learning. That is, the minimization of surprise by means of model parameter exploration may produce an action that opposes the minimization of uncertainty through hidden state exploration when there is high ambiguity or novelty (Schwartenbeck et al., 2019: 25). Particularly, if an outcome is ambiguous due to the ambiguity in a system's mapping from a hidden state to its outcome, then the system infers that this is highly interesting and can be actively learned. Nevertheless, given that the outcome is ambiguous, it is highly aversive from the active inference perspective. For instance, suppose that one decided to watch a sci-fi movie she will enjoy, and what she got is The Matrix, The Matrix Reloaded, and The Matrix Revolutions. Suppose that she saw the Matrix and The Matrix Reloaded and really enjoyed the prequel. Additionally, suppose that she 43 has previously learned that the sequels are never better than the prequels. In this context, which movie should she choose? Given that she saw the first two movies, there is an unambiguous mapping from the hidden state—i.e., a movie, to the outcome—i.e., enjoyment and a prior belief that the prequels are the best. Her inferred action would be to choose The Matrix over The Matrix Reloaded since she

would achieve the outcome through the hidden state exploration. Therefore, active inference results in that she should re-watch The Matrix. However, there is a novel, interesting, and informative option, which is The Matrix Revolutions. In parallel, in her mapping of the structure of the environment, there is a knowledge gap due to the ambiguous mapping that can be filled with model parameter exploration. Thus, active learning leads to that she should watch The Matrix Revolutions. 3.4 The Active Learning Account of Pathologically Chronic Pain and The Active Inference Account of Pain Avoidance Behavior So far, I have referred to the perceptual inference account of physiologically acute pain and pathologically chronic pain that was held until recently. After the progress in the predictive processing literature capturing the intertwinement of perceptual inference and active inference, I have touched on the latest well-establishment of the influence of action in the literature of pain. The up-to-date challenge is the position of the active learning within the framework and its contributory effect on pain. In connection with this, Tabor and Burr (2019) suggest that pathologically chronic pain is formed due to precision weighting of noxious information that eventually leads to the learned optimal precision weighting over time, and that informs a system's model 44 to explore or exploit its environment. Nevertheless, when the tables are turned, this paper does not elaborate on the offerings of the explore-exploit dilemma through

> 1**active inference and active learning to the** emergences **of**

persistent pain and pain avoidance. In order to pave the way for my research, I have pointed out to the exploration-exploitation dilemma within the predictive processing framework, as well. Thus, the question that I investigate here is exactly how active inference and active learning

> 28**play role in the** formation, **maintenance and** treatment **of** pathologically **chronic pain** and pain **avoidance behavior**

. The main motive lurking behind my current inquiry is that to track down the reason causing that physiologically acute pain outwears its purposes to convert into pathologically chronic pain. Additionally, to figure out the ground for the arise of concomitant pain avoidance is another motive of this analysis.

> 1**Active inference and active learning** lay out **a general** ground **for understanding** a system's **exploitative and exploratory**

actions (Schwartenbeck et al., 2019: 35). Following that,

> 1**active inference and active learning** mechanisms promise **a**

clarified

> 1**understanding of goal-directed cognitive deficits within the** scope **of**

psychopathological conditions (Schwartenbeck et al., 2019: 26). Further, the trade-off between exploitative actions and exploratory actions lies at the heart of pain, especially pathologically chronic pain and pain avoidance actions. Particularly, the interchange among hidden state exploration, model parameter exploration, random exploration, and exploitation is governed by their relative 45 precisions. Their relative certainties are products of the

> 46**prediction error minimization**, since **prediction error is a** function **of**

their uncertainties. Therefore, the trade-off between them is governed by minimization of uncertainties. In parallel, when pathologically chronic pain and pain avoidance behavior are casted as Bayesian probabilistic inference problems, they are guided by the minimization of uncertainties. Therefore, the minimization of uncertainty is closely linked with pathologically chronic pain and pain avoidance behavior. In parallel, the trade-off between hidden state exploration, model parameter exploration, random exploration, and exploitation is closely linked with pathologically chronic pain and pain avoidance actions. However, they may result in contrasting actions when an action policy is highly interesting and novel due to its high ambiguity and, at the same time, it is highly aversive because of the same reason—i.e., its ambiguity of the outcome. That is, if the outcomes of a policy are ambiguous respective of high ambiguity about the mapping between the policy and the outcome, then the policy is highly informative. However, if the system is certain regarding that the outcomes of the policy are ambiguous, then the same policy is highly aversive. Importantly, the ambiguity in the mapping of the system must be resolved before the resolution of the uncertainty about the outcomes. Hence, the uncertainty about the model parameterization modulates the effect of uncertainty regarding hidden states on action (Schwartenbeck et al., 2019: 25). 46 On top of these, I propose that, in the

case of pathologically chronic pain, its formation and maintenance result from active learning, while accompanying pain avoidance behavior results from active inference. Consider the following argument. (i) Pathologically chronic pain is a pain experience that originates from a disease or an injury, and lasts for a long time irrespective of the endurance of what causes it. (Ass.) (ii) Pain avoidance behavior is the development and the maintenance of aversion to certain actions to refrain from inducing pain. (Ass.) (iii) Pathologically chronic pain and pain avoidance behavior involve goal-directed exploratory action strategies because the goal that directs them is to minimize unexpected uncertainty—i.e., ambiguity. (Ass.) (iv) A system or an agent with pathologically chronic pain has alterations, which work as stable regularities, within her mappings from the hidden states to their outcomes because of a past disease or injury. (Ass.) (v) If it is uncertain that the outcome of a goal-directed exploratory policy will result in pain due to high ambiguity regarding the agent's mapping between the hidden state to the outcome, then this policy is highly informative, interesting and novel—i.e., the model parameter exploration. (Ass.) (vi) Active learning is updating the parameters of a system's or an agent's generative model to produce inferences that better reflect the incoming information. (Ass.) 47 (vii) Therefore, pathologically chronic pain involves the model parameter exploration. The mapping of the system or the agent with pathologically chronic pain gets certain gradually through active learning. (i, iii, iv, v, vi) (viii) If it is uncertain that the outcome of a goal-directed exploratory policy will result in pain, and the agent's mapping between the hidden state to the outcome is unambiguous; then this policy is highly aversive. (Ass.) (ix) Active inference is carrying out actions to sample input that better captures what is inferred either for epistemic purposes or achieving an outcome. (Ass.) (x) Therefore, pain avoidance behavior originates as the hidden state exploration through active inference. (ii, iii, viii, ix) (xi) Therefore, the same uncertainty in the outcomes of an action policy results in both the emergence of pathologically chronic pain and pain avoidance behavior. Pain avoidance behavior accompanies pathologically chronic pain. (v, vii, viii, x) (xii) Physiologically acute pain is a nociceptive or inflammatory experience that originates from a disease or an injury, and lasts for a short time with reference to the agent's gradual healing, which indicates no new stable regularities laid out biologically. (Ass.) (xiii) The action occurs as a result of physiologically acute pain involves exploitative action strategy. (Ass.) (xiv) If there is high ambiguity regarding the agent's mapping between the hidden state to the outcome in addition to that active inference is broken due to a disease 48 or an injury, which resulted in physiologically acute pain, then through active learning new biologically stable regularities are formed and physiologically acute pain turns into pathologically chronic pain. (Ass.) (xv) Therefore, the trade-off among the model parameter exploration, the hidden state exploration, and the exploitation is governed by the uncertainty minimization within the predictive processing framework. (vii, x, xiii, xiv) (xvi) Pathologically chronic pain and its accompanying pain avoidance behavior are psychopathological conditions. (Ass.) (xvii) Therefore,

> 1**active inference and active learning** mechanisms promise **a**

clarified

> 1**understanding of** the **goal-directed cognitive deficits within the** scope **of**

psychopathological conditions. (xii, xvi) 3.5 The Future Directions The thesis paves the way for three future directions in distinct disciplines such as philosophy, neuroscience, and medicine. First, given that pain is a complex experience, its modulators also enclose thought, beliefs and desires. They may have impacts on the emergence, maintenance, and management or treatment of pathologically chronic pain. Hence, the predictive processing framework is required to explain such propositional mental states (Williams, 2020). Second, although the computational approaches to cognition has a convincing advantage over the neuroscientific approaches to cognition, the neural underpinning 49 of the computational activities in the human brain is necessitated for a full-blown apprehension of cognition. In parallel, the brain

> 26**oscillations and** the **synchrony at different frequencies** may **provide** further **evidence on information flow across areas** of **the**

human brain, which underlies the computational processes. The neuroscientific approach to cognition combined with the prediction error framework hypothesizes that the information refers to the predictions and the prediction errors (Ploner, Sorg & Gross, 2017). Beta (12-30 Hz) frequency reflects the prior predictions and takes role in feedback signaling in the descending pathway of pain (Arnal & Giraund, 2012). Further, the prediction errors are reflected by gamma (30-100Hz) frequency and serves feedforward signaling in the ascending pathway of pain (

> 24**Pinheiro, Queirós, Montoya, Santos, Nascimento, Ito, Silva, Nunes Santos, Benevides, Miranda, Sá & Baptista, 2016**

). In the pathologically chronic pain cases, there is an abnormal increase in theta (4-8 Hz) frequency (Stern, Jeanmonod & Sarnthein, 2006; Sarnthein, Stern, Aufenberg, Rousson & Jeanmonod, 2006), however its role

in the predictive processing framework has not been refined yet. It may be hypothesized that theta frequency refers to posterior inference concerning pathologically chronic pain. Third, having said that pain is fundamentally about action, the cognitive behavioral therapy (CBT) may promise noteworthy pain treatment methods. CBT is a kind of therapy that lies at the intersection of multiple disciplines such as psychology, psychiatry, pharmacology, and so forth (Tang, 2018). Its theoretical basis is on the 50 learning models such as the classical Pavlovian (habitual) conditioning, the operant (instrumental) conditioning, Rescorla-Wagner learning, associative learning, and so on (Tabor & Burr, 2019: 54). It adds the influence of beliefs and appraisals in the learning models. In addition, it recognize the effect of behavior on psychological responses. In parallel, the psychopathological conditions such as pathologically chronic pain can be treated by means of CBT. However, it necessitates that these learning models and active learning must find a middle ground. 51 CONCLUSION In this thesis, I disputed that the computational approaches like the predictive processing has a great advantage over the neuroscientific approaches

17**when it comes to** an efficient **understanding of the human**

brain. Peculiar as is pain, I held that pain worths to be studied philosophically because (i) it is not mechanistically explicable, (ii) it is not objectively identifiable, and (iii) it is not treatable but manageable according to what is currently known. Additionally, I made cases for evaluativism, imperativism, and psycho-functionalism regarding their explanatory power on pain. Yet, all three failed at different points. Further, I argued that the predictive processing framework holds out high hopes of refined comprehension of the goal-directed cognitive deficits within the scope of psychopathological conditions such as pathologically chronic pain and pain avoidance behavior. Particularly, I revolved around the questions (I) why physiologically acute pain overstays its protective function to become a pathologically chronic pain and (II) why pain avoidance behavior accompanies pathologically chronic pain. I made use of the explore-exploit dilemma to respond these inquiries. I inferred that (1) pathologically chronic pain comprises the model parameter exploration through active learning, (2) pain avoidance behavior involves the hidden state exploration through active inference, (3) physiologically acute pain results in exploitative action. I proposed that (a) the very same uncertainty in outcomes of an action strategy entails both pathologically chronic 52 pain and pain avoidance behavior, and (b) the high ambiguity in a system or an agent's internal mapping between hidden states to outcomes and the broken active inference because of a disease or an injury entail the transformation of physiologically acute pain to pathologically chronic pain. Thus, pain avoidance behavior accompanies pathologically chronic pain, and physiologically acute pain leaves its protective and adaptive purposes to turn into non-protective and maladaptive pathologically chronic pain. Moreover, the thesis has three future directions: (A)the predictive processing framework may bring forward an account for thoughts, beliefs, and desires, which modulate pathologically chronic pain, (B) the brain oscillations such as theta and the synchrony at different frequencies may require an investigation and may offer further evidence on information flow across areas of the human brain with pathologically chronic pain, (C) CBT may assure pathologically chronic pain treatment, if the learning models grounding CBT and active learning underpinning the predictive processing framework needs to settle a dispute. 53 REFERENCES Adams, R., Brown, H., & Friston, K. (2014). Bayesian inference, predictive coding and delusions. AVANT. The Journal Of The Philosophical-Interdisciplinary Vanguard, V(3), 51-88. Ali, S. A., Begum, T., & Reza, F. (2018). Hormonal Influences on Cognitive Function. The Malaysian Journal of Medical Sciences: MJMS, 25(4), 31–41. Appleton J. (2018). 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Pathological pain stems from injuries or diseases such as strokes, diabetes, amputations, spinal cord injuries, or multiple sclerosis (C). Nociplastic pain such as fibromyalgia arises from no particular reason (D). 62 Figure 2. The classification of pain based on persistency. Pain is either acute or chronic. What makes a pain acute are that it lasts less than six months-i.e., short-lived, that it has a function in protection of the bodily integrity, and that its function is an adaptation that results in the survival of a system or an agent (A). Contrarily, what makes a pain chronic are that it lasts more than six months or a life time, that it lacks function in the survival of a system or an agent, and that it is a maladaptation of a system or an agent (B). 63 Figure 3. The key elements of Bayesian Brain Hypothesis. Beliefs or inferences are statistical probability distributions over the unknown sources of states. A prior belief is a belief that is encoded prior to a sensorimotor information. A sensorimotor likelihood is a current sensorimotor information. Sensorimotor likelihood is noisy information. A prior belief that will match with a sensorimotor likelihood has also a subjective uncertainty. The difference between the precision of a prior belief and the

40**precision of the** actual sensorimotor **input** refers **to the precision of**

prediction error (PE). The precision of the prediction error is weighted and set off for the formation of a refined belief called a posterior belief. 64 Figure 4. The influence of precise source of information on posterior belief.

44**The relative precisions of the prior** belief **and the**

sensorimotor likelihood contribute to the precision of the posterior belief. If an inference is relatively more

precise, then it has a greater impact on the formation of the posterior belief. The precision of an inference is shown as relatively more narrower probability density. For example, the precision of the sensorimotor likelihood remained as constant, if the precision of the prior belief is relatively higher than the precision of the sensorimotor likelihood, then the prior belief contributes more in the formation of the posterior belief, and the probability density of the posterior belief is drawn toward the prior belief (A). However, if the precision of the prior belief is relatively lower than the precision of the sensorimotor likelihood, then the the sensorimotor likelihood contributes more in the formation of the posterior belief, and the probability density of the posterior belief is drawn toward the sensorimotor likelihood (B). 65 Figure 5. The decoupling of the actual sensorimotor information from the subjective experience of a system or an agent. Within the predictive processing framework, there is a decoupling between an actual sensorimotor information and a prior belief of a system or an agent. Suppose that there is an actual threatening sensorimotor information in the environment. If there is a relatively precise prior belief that reflects the bodily integrity and safety of the system or the agent, then although there is a threatening current sensorimotor information, the posterior belief, influenced more by the prior belief, reflects the bodily integrity and safety (A). Contrarily, the prior belief is relatively less precise than the relative precision of the sensorimotor likelihood, then the posterior belief is relatively closer to the sensorimotor likelihood, and it reflects the threat towards the bodily integrity. 66 Figure 6. The hierarchical probabilistic internal generative model. It generates inferences that results from the hidden external states, and, even, in the absence of its external stimulation by the hidden states. It is formed over time to reflect a precise representation of the body and the environment. There is a hierarchy of inferences. The prior beliefs are generated by the relatively higher mental states. The sensorimotor likelihoods are created by the relatively lower mental states, and they carry weight towards the relatively higher mental states because of the mismatch between the sensorilikelihoods and the priors. 67 Figure 7. The classification of action strategies. Mainly, there are two types of action strategy: exploratory action strategy and exploitative action strategy. An exploratory action policy is information-driven. That is the role of an exploration is to gain information. There are two sub-types of exploration: random exploration and goal-directed exploration. A random exploratory action policy is to randomly sample information that is available in the body and the environment, which results in updating in the generative model of a system or an agent. It occurs through active inference (A). There are two kinds of goal-directed exploration: the hidden state exploration and the

1**model parameter exploration**. The **hidden state exploration is**

to gain information about the source of a sensorimotor information that causes an observation by means of active inference (B), whereas the model parameter exploration is to gaining information for generating the mapping from a hidden state to its observation through active learning (C). In contrast, an exploitative action policy is outcome-driven. That is, it occurs to achieve a certain observation via active inference (D). 68 Figure 8. The classification of uncertainty kinds. Mainly, there are two kinds of uncertainty: expected uncertainty and unexpected uncertainty. The expected uncertainty stands for risk, while the unexpected uncertainty refers to ambiguity. Exploitative action strategy is sensitive to risk (A). However, exploratory action strategy is sensitive to ambiguity (B). 69 Figure 9. The trade-off among the action strategies. Whether there is an ambiguity within a system or an agent's model's mapping from a hidden state to an observation or not, and whether the observation is ambiguous or not determine the system or the agent's action policy. Additionally, whether the ability of the system or the agent to make an active inference or to do active learning has influence over the trade-off among the action strategies. For instance, active learning may be broken by the lack of stable regularities in the body and the environment. As another example, active inference may be broken by the lack of activity in a certain body part. In parallel, stepping on lego pieces may need to the hidden state exploration for the observation of the lego pieces on the floor, while multiple sclerosis may need to the model parameter exploration for the precise representation of the current body form. 70

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> 5**M.A., Department of Philosophy Supervisor: Asst. Prof. Dr. István Albert Aranyosi June** 2021 Pain as **the**

most enquired philosophical theme is a complex experience, which includes sensation, emotion, motivation, cognition, and social interaction. However, there is not a single overarching philosophical theory that accounts for all the dimensions of pain. The most overlooked discussion of pain is on its motivational aspect; yet, it is indispensable for an integrated understanding of pain. Also, its least debated area is the substantial relation between pathologically chronic pain and action. In this thesis, I attempt to investigate why physiologically acute pain outlasts its purposes to transform into pathologically chronic pain and why pathologically chronic pain is accompanied by pain avoidance behavior by drawing inferences from the explore-exploit dilemma. I also examine the related pain theories addressing their i failures in answering these questions. I conclude that analyzing pathologically chronic pain and pain avoidance behavior within predictive processing framework (1) provides an active learning account for pathologically chronic pain, (2) ensures an active inference account for pain avoidance behavior, (3) allows an active learning account for pain avoidance behavior only if certain conditions are met, and (4) points out the disparate action strategies are accountable for pathologically acute pain, pain avoidance behavior, and physiologically acute pain.

Keywords: Active Inference, Active Learning, Explore-Exploit Dilemma, Pain Avoidance Behavior, Pathologically Chronic Pain ii ÖZET ÖNGÖRÜYE DAYALI İŞLEME ÇERÇEVESİ İÇİNDE PATOLOJİK KRONİK AĞRI VE AĞRIDAN KAÇINMA DAVRANIŞI Demirkaya, Eyşan

4**Yüksek Lisans, Felsefe Bölümü Tez Danışmanı: Dr. Öğr. Üyesi István Albert Aranyosi**

Haziran 2021 Ağrı, en çok araştırılan felsefik temalardan biri olarak, algı, duygu, motivasyon, biliş ve sosyal etkileşimleri içeren kompleks bir deneyimdir. Fakat ağrının tüm boyutlarını kapsayan bir felsefe teorisi bulunmamaktadır. Ağrı tartışmalarında en çok gözardı edilen ağrının motivasyon boyutudur; bununla birlikte motivasyon, ağrının bütüncül bir anlayışı için temel bir bileşendir. Ayrıca, ağrının motivasyon yönünün en az tartışılan alanı patolojik kronik ağrı ile eylem arasındaki önemli ilişkidir. Bu tezin esas amacı fizyolojik akut ağrının fonksiyonlarını kaybederek neden patolojik kronik iii ağrıya dönüştüğüne ve ağrıdan kaçınma davranışının patolojik kronik ağrıya neden eşlik ettiğine keşfet-faydalan ikileminden çıkarımlarda bulunarak cevap aramaktır. Bu tez aynı zamanda ilgili ağrı teorilerini ve onların bu soruları cevaplamadaki başarısızlıklarını inceleyecektir. Bu tezden çıkarılan sonuçlara göre, öngörüye dayalı işleme çerçevesi (1) patolojik kronik ağrıyı aktif öğrenme ile açıklar, (2) ağrıdan kaçınma davranışını aktif çıkarım ile izah eder, (3) ağrıdan kaçınma davranışını yalnızca belirli koşullar sağlandığında aktif öğrenme ile ifade eder ve (4) farklı eylem stratejilerinin patolojik kronik ağrıdan, ağrıdan kaçınma davranışından ve fizyolojik akut ağrıdan sorumlu olduğuna işaret eder. Anahtar Kelimeler: Ağrıdan Kaçınma Davranışı, Aktif Çıkarım, Aktif Öğrenme, Keşfet-Faydalan İkilemi, Patolojik Kronik Ağrı

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39**One approach to this question is to** scan the **brain**

, which, falls into the scope of neuroscience. Scanning is a way of producing the detailed images of the human brain by the magnetic fields and radio waves (MRI and fMRI) or X-rays (CT) or electrical charges (EEG) (Glover, 2011). Yet, these scanning techniques are not nearly good enough to capture all the activities in the human brain. There are two reasons for this situation. Initially, there are technical challenges in scanning such as noise signals, image distortions, and signal dropouts. Secondly, the human brain is complex. There are approximately

31**100 billion neurons in the human brain** while these **are in**

communication with one another through one million billion synapses ("Brain Facts and Figures", 2021). Signals are fired reaching to one thousand times every second. This implies that up to one quadrillion signaling events occur each second. What's more, there is a lot more to the human brain than the neuronal cells and signals. There are 10- to 50-fold more non-neuronal cells including the glial cells, immune cells, neurotransmitters, neuromodulators, and hormones (Herculano-Houzel, 2012: 1). Some glial cells such as astrocytes, microglia, and oligodendrocytes have a role in memory formation (Hertz & Chen, 2016: 1). To give an example, GABA neurotransmitters are responsible for pain relief (Yowtak, Wang, Kim, Lu, Chung, & Chung, 2013: 2469). The impact of immune T cells on stress responsiveness 1 exemplifies immune cells' implications to the human brain functions (Morimoto & Nakajima, 2019: 1). For instance, the neuromodulator histamine has a vital function in learning (Tasaka, 1994: 27). Also, androgen is linked with visuospatial ability (Ali, Begum, & Reza, 2018: 34). Further, the human

8**brain is influenced by** the **other** bodily **parts** such as **heart nerves** and **gut**

microbiome. For example, heart nerves affect attention and motivation (McCraty, Atkinson, Tomasino, & Bradley, 2009:16). Another example, a type of bacteria called Lactobacillus within the human gut microbiome increases the appetite for sugar (Leitão-Gonçalves, Carvalho-Santos, Fioreze, Anjos, & Baltazar,, 2017: 1; Appleton, 2018: 28). Through the efforts of researchers from various disciplines encapsulating the microbiologists, geneticists, biochemical engineers, chemists, medical doctors, and psychologists, a basic understanding of their functions at small scales is already known but an understanding of their functions at larger scales is still elusive. A new promising neuroscientific method, which is cutting the brain into a number of small

8**slices and** then **scanning them with a high resolution electron microscope**

is used recently (Zhu, Cizeron, Qiu, Benavides-Piccione, Skene, Fransèn, Komiyama,& Grant, 2018). The novelty of this approach comes from its surpassing challenges in scanning. In particular, a cubic millimeter of the mouse brain containing a hundred thousand neurons with a billion connections was cut into 25 thousand slices (Zhu et al., 2018: 781).

8**Five electron microscopes** scanned them **for five months collecting more than 100 million images**

. Additionally, the formation of a 3D model out of 100 million images of a single cubic millimeter of the mouse brain took three months. 2 Further, the data gathered from it took

8**up 2 million gigabytes of cloud storage. To** scan **the** human **brain**

, this whole endeavor has to be replicated a million times, since the human brain has around one million billion synapses. Consequently, complete data of the human brain would take thousands of years and two million petabytes. Surprisingly, these are just for mapping synapses. For a complete scanning of the human brain, each influencer of the human brain must be mapped out. More importantly, this would take millions of years and more data storage than that on the Earth. On top of that, all this effort provides a static mapping of the human brain instead of an active wiring of an agent. In order to reach an understanding of an active agent, the laws and rules governing the activity of the human brain at micro- and macro-level are necessary. As opposed to these neuroscientific approaches, there is a propitious computational approach called the predictive processing. Particularly, it suggests that it might not be necessary to scan everything in he human brain and its influencers. The human brain can be simplified into the probabilistic internal generative models that could match the human brain regarding its functions. To exemplify, a probabilistic generative model of the human brain can learn or false learn, remember or forget, imagine or dream, develop an action or remain inactive, and so forth. By simplifying the human brain into the generative models, it can be attained how the static mapping of the human brain leads to an active agent (Friston, 2010; Clark, 2013; Hohwy, 2013). However, similar to the human brain's development of myriad disorders, a generative model can develop a number of maladies. Specifically, if a probabilistic generative 3 model of the human brain is damaged in any of innumerable ways, then the agent may be in persistent pains, intermittent hallucinations, or endless delusions. From the faculties of the human brain to its disorders, maybe, the most peculiar thing about the human brain is pain. There are three reasons for that: (i) it is not a process that can be explained mechanistically because the human brain's pain answer is distributed across multiple brain areas (Corns, 2015: 3), (ii) it is not a proper scientific subject because it is indicated only by subjective report (Corns, 2018:1), (iii) the success rate of pain targeted treatments is not 100% implying that patients who suffered from pain will continue to suffer, and that pain management overrules pain treatment in the medical arena (Main, Spanswick & Bartys, 2000). Yet, the computational approach to the human brain may promise innovative advancements particularly in understanding the emergences, maintenances, and treatment of experiences such as pain. Thus, in this thesis I investigate pathologically chronic pain and pain avoidance behavior within the predictive processing framework. Specifically, I ask

48**why physiologically** acute **pain outlives its** purposes **to** become **pathologically** chronic **pain**

, and why pathologically chronic pain is accompanied by pain avoidance behavior. I argue that by casting physiologically acute pain, pathologically chronic pain, and pain avoidance behavior as Bayesian probabilistic inference problems, different mechanisms having roles in the development, continuation, and treatment of distinct pains and behaviors emerged. 4 These mechanisms encapsulate perceptual inference, active inference, and active learning. I aim (i) to expand the predictive processing framework to

pathologically chronic pain and pain avoidance behavior associated with the persistent pain by examining the explore-exploit dilemma, (ii) to make it functionally-explicable, (iii) to render it scientifically objectively comprehensible, and (iv) to pave the way for its treatment. In Chapter 1, I start by reviewing the pain theories that come to the front in the Philosophy of Mind, which are composed of evaluativism, imperativism, psycho-functionalism. I then discuss some of the worries that gained prominence in the literature. I also discuss whether or not these theories could tackle the main questions of the thesis. Chapter 2 shifts the conversation on pain to the review of the predictive processing

> 35**framework. In this chapter, I** discuss **the** conceptual background **of** the **framework**. That **is**

, I demonstrate how this framework roots from Bayesian Brain Hypothesis and the Predictive Coding Theory. I conclude the chapter by overviewing perceptual inference, active inference, and active learning. Throughout Chapter 3, I examine why physiologically acute pain outstays its functions to turn into pathologically chronic pain, and why pathologically chronic pain is associated by pain avoidance behavior. I claim that the main reason that distinct mechanisms take part in gaining information and producing actions regarding 5 physiological acute pain, pathologically chronic pain, and pain avoidance behavior is because of the influence of discrete levels of uncertainty on them. Through the explore-exploit dilemma, I draw the observation that

> 1**active inference and active learning** lead **to the emergence** and the preservation **of**

pain avoidance behavior and pathologically chronic pain, respectively. I also demonstrate how the perceptual inference explains the sensory and perceptual character of both physiologically acute pain and pathologically chronic pain. Before I conclude, I revolve around the implementations of the thesis in the scope of philosophy, neuroscience, and psychiatry. 6 CHAPTER I PAIN What is taken for granted regarding pain is that it is a complex, convergent, and multidimensional experience (Krahe, Springer, Weinman, & Fotopoulou, 2013). It encapsulates sensation, emotion, motivation, cognition, and social interaction. That is, it is modulated by bodily sensations (i.e., nociception), affect (i.e., attitude), evaluation (i.e., appraisal), action (i.e., volitional or involuntary behavior), and cognitive processes (e.g., attention, expectancy, or mood) and interpersonal interactions. It has phenomenal character, like other experiences with bodily sensational component, such as hunger, tickles, and itches. Its affective character is, mostly, unpleasant although there are cases of pleasant pain as well. When it is unpleasant, it motivates the body to take an action to mitigate it. If it is pleasant, then an action is taken by the body to protract it. Yet, little is known about the nature of pain and its biological markers in the human brain (Corns, 2016: 2950; Corns, 2018: 1). In the first instance, pain may be 7 physiological, pathological, or nociplastic (Woolf, 2010: 3742). Physiological pain is crucial for physiological, adaptive and protective system of the body. It detects the noxious incoming data and tissue damage, and signals for maintaining the integrity of the body. In the former case, this kind of pain is also called nociceptive pain because it relies on nociception (Figure 1A). Yet, if it is the latter, then it is also named inflammatory pain because it originates from inflammation on tissues due to damaging (Figure 1B). The adaptive and protective function of physiological pain calls for action such as relatively simpler behavior like withdrawal reflex or relatively more complex behavior like avoidance behavior. Consider an infant's encounter with the burn of the fire of a candle, the cut of the sharp edge of a knife, or the ice burn of the coldness of an ice cube. After the very first experience of the infant with the hot, sharp or cold objects, a withdrawal reflex may be demanded, whereas the following experiences may demand an avoidance behavior. Alternatively, an inflammation on the body as in the case of rheumatoid arthritis may call for an avoidance behavior. However, pathological pain is not protective, and it is maladaptive (Woolf, 2010: 3742). It is dysfunctional. It stems form malfunctioning of the nervous system because of a disease or a disorder damaging or irritating the nervous system. It is also mentioned as neuropathic pain (Figure 1C). In addition, nociplastic pain is not protective (Woolf, 2010: 3742). It is maladaptive and dysfunctional, as well (Figure 1D). Unlike pathological pain, it does not derive from a disease or a disorder. Consider a nociplastic pain due to fibromyalgia. 8 Additionally, a physiological pain may be acute or chronic (Figure 2A and 2B). If it is acute, then it is short-lived—i.e., lasts less than six months, while if it is chronic, it persists—i.e., lasts more than six months (Grichnik & Ferrante, 1991:217). Further, acute pain is treatable, whereas chronic pain is irrespective of a current disease or disorder. Consider physiological acute tissue trauma pain resulted from stepping on a lego piece. Alternatively, consider physiologically chronic pain sprung from osteoarthritis. However, pathological pain may be acute or chronic. Consider pathological chronic pain brought about by stroke, spinal cord injury, multiple sclerosis, amputation, or diabetes. What's more, whether a pain is physiological, pathological, or nociplastic, what its matrices, biological processes, or neurological activation patterns are difficult to track down because when such neuroscientific methods are used, multiple areas of the human brain light up (Garcia-Larrea & Peyron, 2013: S30). That is, brain is not modular when it comes to pain. Apart from the nature of pain and its biological markers in the human brain, from whether or not pain is a natural kind to whether it is a mental experience, a bodily condition, or a representation, the controversies are numerous (Corns, 2018: 14). Further, if it is a representation, then the kind of representation is controversial. The neuroscientific approaches and the computational approach to the human brain, which aim to explain how an inactive wiring of the human brain generates an active agent, share an assumption. It is called strong representationalism according to which all mental states and processes are representational (Armstrong,

1961). In detail, it argues

42**that a mental state is** exclusively **determined by its**

intentional content (Dretske, 9 1995; Tye, 1995). In parallel, a representation is a mental object that bears an informative intentional content. For example, physiologically acute pain represents a physiological disturbance. Strong representationalism grounds these approaches to the human mind and has an advantage over its weaker version holding that the intentional content does not ground the mental state (Block, 1990) because it can explain all mental states and processes with qualitative character by reducing the phenomenal character to the intentional content. A qualitative character refers to "what it is like for one to be in that mental state" (Block, 1990). The bodily sensations such as hunger, tickles, itches, and pain have qualitative character. They pose a challenge for the weaker version of the representationalism. Particularly, what it is like to be in a physiologically acute pain experience for an agent cannot be accounted by the weak version of representationalism. However, the strong version of representationalism is not free of challenges. The opponents of the strong representationalism attack to pain's affective and motivational characters. Initially, all mental states and processes with affective character present a challenge for the strong version of representationalism. For instance, pain is affective in its nature. It is felt as either pleasant or unpleasant. That is, pain involves an attitude. Yet, the stronger version of representationalism cannot account for the affective character of pain. Additionally, pain motivates an agent to take an action. Yet, this motivational character of pain is not accounted by the strong 10 version of the representationalism. To explain the phenomenal, sensory, affective, and motivational characters of pain, evaluativism, imperativism, and psycho-functionalism emerge. 1.1 Evaluativism Regarding Pain The evaluative perceptualist theory regarding pain argues that pain is a perception. That is, pain has a modality-specific character called sensory character. This sensory character refers to the bodily condition. Evaluativism is, also, an intentionalist representationalist theory, which claims that pain represents a sort of bodily disturbance. This object of perception has an intentional content. It indicates that "something that is sensory—i.e., a kind of physiological disturbance, is the case". In this regard, it is an indicative content. In parallel, it needs to satisfy an accuracy condition. That is, it either affirms or denies that something is the case. Aside from its sensory character, evaluativism holds that unpleasantness or pleasantness of pain—i.e., its affective character, forms evaluative content of the representation (Bain, 2013). Consequently, according to evaluativists, there is a single representation composed of two distinct contents, which are called indicative content and affective content. Suppose that one drinks a glass of sour milk, and that therefore, she feels a specific type of pain in her stomach. Her pain represents that (i) a physiological disturbance in her stomach is the case, and (ii) this particular disturbance is unpleasant for her. 11 However, there are, mainly, three worries about evaluativism regarding pain. First, the messenger-shooting objection comes against the perceptualist aspect of evaluativism (Jacobson, 2013). Particularly, how evaluativism, like any perceptualist theory, explains the motivational character of pain appears to be problematic. It suggests that pain as a representation is equivalent to a messenger that informs the perceiver about the bodily disturbance. Given that pain's motivational character is what drives the perceiver to eliminate that pain when it is unpleasant for the perceiver, representing the physiological disturbance that motivates to get rid of the pain is equal to shooting the messenger. Yet, it is not clear that how shooting the messenger eliminates the bodily disturbance. For example, one receives an e-mail from her downstairs neighbor informing about the leakage from her ceiling that is unpleasant for her downstairs neighbor and her. In this setting, the e-mail functions as a representation with an informative indicative content and an affective content. Nevertheless, this e-mail does not give her a motivation to fix the leakage coming from her apartment. Additionally, deleting the e-mail does not mean that the leakage is fixed. Analogously, pain perception does not motivate its perceiver to eliminate the bodily disturbance. The second objection attacks evaluativism's representationalist aspect. It is called the problem of semantic focus (Aydede, 2009). Specifically, whether the semantic focus is on pain itself or on the semantic concepts that are related with the bodily disturbance is problematic. It proposes that when a bodily disturbance is perceived by a perceiver, the semantic concept PAIN is not applied to the bodily disturbance. The 12 semantic focus is already on the pain experience itself. For instance, in a scenario, in which one perceives a traffic light, vision is the modality, and the color information is the information that is specific to the visual modality. The object of this perception is the traffic light. At the same time, this perception leads to the attachment of the semantic concepts such as RED, YELLOW, or GREEN, which become parts of the object of the perception. The last objection attacks evaluativism's intentionalist aspect. It is concerned with the accuracy condition of the representation's indicative content. That is, the necessary conditions that make the bodily disturbance an unpleasant pain accurate or inaccurate are still unclear (Corns, 2018: 6). Particularly, in evaluativism, a representation indicates that something is the case. In this respect, it has an indicative content that contains an accuracy condition. In other words, whether something is the case or not implies the accuracy condition of the representation. If a pain is a representation that accurately represents that the bodily disturbance is the case, then it is misrepresentation that inaccurately represents that the bodily disturbance is the case. It is possible that pain is a misrepresentation as well as that it is a representation. That is, whether all pains are misrepresentations or some pains are representation is not explicit in evaluativism. In the case of phantom pains of amputees, for example, a pain felt on an amputated limb is an inaccurate representation of a bodily disturbance. Hence, the phantom pain exemplifies a pain that is a misrepresentation. Yet, a pain felt on a healthy limb of the amputee due to accidentally hitting it on a wall may exemplify a pain as an accurate representation of the bodily disturbance. 13 In connection with the first and the third objections, I have an additional worry. If

evaluativism is true, then how physiologically acute pain turns into pathologically chronic pain is problematic. In detail, pain is an overarching term that involves mainly physiologically acute pain and pathologically chronic pain. Pain caused by a broken leg bone is an example of a physiologically acute pain, while a neuropathic pain is an instance of pathologically chronic pain. Both are felt in certain areas of the human body with varying degrees of intensity. The acute and chronic pain perception differs from each other with respect to their motivating force for an action and their accuracies regarding their felt places and intensities. In an evaluativist setting, they appear to be problematic in some ways. First, if evaluativism is true, then physiologically acute pain is purposeful—i.e., it has a sort of utility for the perceiver such as warning the human body from of injury and motivating her to take an action. Second,

> 14**if evaluativism is true, then** physiologically acute **pain is** an accurate **representation**

of either internally- or externally-caused sensation of the bodily disturbance. At the same time,

> 14**if evaluativism is true, then** pathologically chronic **pain is**

, also, purposeful. Supplementally,

> 14**if evaluativism is true, then** pathologically chronic **pain is** an accurate **representation**

because it accurately represents a sensation of the bodily disturbance. However, it is not the case that pathologically chronic pain is purposeful and an accurate representation of a bodily disturbance. Therefore, evaluativism does not account for what results in a misrepresentation that was once a representation and the lack of motivation for an action-taking that was once there. 14 1.2 Imperativism Regarding Pain The imperative representational theory of pain holds that pain represents an imperative. This representation—i.e., the command, has an intentional content. In parallel, this intentional content forms the command's imperative content. Different from evaluativism, it represents that "something is to be done" in imperativism (Klein, 2015). In this respect, it comprises information about an action performed by the agent. The action may be either to stop doing something or to protect the human body. Additionally, as opposed to the accuracy condition of the indicative content in evaluativism, the imperative content has a satisfaction condition. That is, it either satisfies or dissatisfies that something is to be done. In parallel, pain motivates doing or acting on something directly through its imperative content (Hall, 2008: 530). However, some pains may represent an unsatisfiable or an already satisfied command. Consider headaches, neuropathic pains, and phantom pains as examples to such pains (Martinez, 2015). There are mainly three arguments against imperativism with regard to pain. The first argument against imperativism with regard to pain is concerned with the imperative content of pain. In particular, it argues that there are some pains that do not motivate their agents to take actions, and they are problematic for imperativism. Consider that morphine pain and pain after lobotomy do not result in action (Grahek, 2007). The second argument against imperativism is about the pain's imperative content, which is called the problem of authority (Bain, 2011: 180). Precisely, it contends that a command does not motivate an agent to execute an action concerning pain, and there 15 is a problem of authority in imperativism. What motivates a system or an agent to take an action is the reason, which gives the authority to the system or the agent herself. The third argument against imperativism concerning pain is about the sensory and affective characters of pain (Corns, 2018: 9). Clearly, it asserts that imperativism concerning pain does not account the pain's sensory and affective characters, although it reflects the motivational aspect of pain. In addition to these three worries about imperativism regarding pain, I have an additional worry. How physiologically acute pain turns into pathologically chronic pain is problematic for imperativism similar to that it is the case for evaluativism. To be specific, what changes the satisfaction command of an acute pain to the satisfaction command of a chronic pain is unclear in imperativism. That is, what determines the move from being satisfiable to being unsatisfiable is elusive. In other words, the condition for an unsatisfiable pain is lacking in imperativism. For instance, if evaluativism is true, then a phantom pain necessarily remains unsatisfiable. However, this is not the case in that Ramachandran's mirror-box approach to phantom pain satisfies such pains (Ramachandran, 1998). 1.3 Psycho-functionalism Regarding Pain Contrary to evaluativism and imperativism, psycho-functionalism is a theory against the strong representationalism. It holds that pain represents a kind of bodily disturbance as its sensory intentional indicative content. Unlike the evaluativists and the imperativists, however, the psycho-functionalists reject the argument that the 16 affective character of pain has an intentional indicative content because because it has a qualitative character and a functional character irrespective of the accuracy condition of a representation's content. That is, regardless of whether there is a representation or misrepresentation, it functions in the development of the affective-

> 41**motivational character of pain**. Instead, **the** affective **and motivational** characters **of**

pain arise from the processing of the representation's indicative content. This is called m-processing occurring at sub- personal level. The m-processing of a sensory information leads to either attraction or aversion. This forms phen-desiring, which refers to the formation of desires regarding either pleasant or unpleasant content. In addition, m-processing results in phen- beliving. That is, it has a role in the formation of beliefs concerning the sensory information. Further, m-processing which is composed of phen-desiring and phen- beliving shapes reason for action. If there weren't a reason for an action, then a command would not motivate an agent to take an action. Also, if there is a reason for an action, there is no need for a command. Therefore, m-processing gives rise to actions, desires, and beliefs without an affective intentional content, as in evaluativism, and without a command, as in imperativism. Against psycho-functionalism, there is one major worry. It is about its sub-personal aspect. To be specific, it argues that sub-personal level m-processing does not elucidate the normative reasons for action (Bain, 2013). In order to explain the normative motivations to act, personal level processing is necessary. Additionally, I 17 have a further worry about psycho-functionalism. Similar to the case for both evaluativism and imperativism, the way, in which a physiologically acute pain becomes a pathologically chronic pain, creates a problem for psycho-functionalism. Namely, if psycho-functionalism is true, then all agents with pathologically chronic pains must have the same sub-personal and functional processing. Otherwise, an agent with a slight individual difference in the sub-personal and functional processing does not count as having pathologically chronic pain. It is, yet, the case that pathologically chronic pain manifests individual differences from one agent to another although these individual differences are not accounted scientifically at the sub-personal level. Therefore, psycho-functionalism cannot explain the individual differences of the agents with pathologically chronic pain. 18 CHAPTER II THE PREDICTIVE PROCESSING FRAMEWORK From the conversation on pain, I move the dialogue toward the conceptual background of the predictive processing framework before examining pathologically chronic pain and pain avoidance behavior. Particularly, this framework roots from Bayesian Brain Hypothesis and the predictive coding theory. Nevertheless, the fame of the predictive processing framework comes from perceptual inference, active inference, and active learning.

5**Thus, I start by providing an overview of**

Bayesian Brain Hypothesis and the predictive coding theory. Then, I dwell into perceptual inference, active inference, and active learning before inquiring why physiologically acute pain outlives its protective and adaptive functions to turn into pathologically chronic pain and why pain avoidance behavior and pathologically chronic pain are associated. 2.1 Bayesian Brain Hypothesis One of the approaches to cognition is Bayesian Brain Hypothesis. It is an overarching hypothesis composed of several different models to account for divergent domains 19 and distinct levels of cognition. Importantly, it is the underlying hypothesis of the

24**predictive processing framework. The** main tenet **of this**

hypothesis is that

34**brain is a Bayesian inference machine (Friston, 2010). The**

underlying principle of this view is that the brain has

7**only indirect access to the** bodily **internal** states **and** the environmental **external**

states. Consequently, it must infer the sources or causes of these states. That is, brain generates probabilistic internal inferences following Bayes' rule. Then, what is a Bayesian probabilistic inference? A Bayesian inference, prediction, belief or information is a statistical probability distribution over an unknown source or cause of a state (Friston, 2010). In that sense, Bayesian beliefs are different than the explicit propositional beliefs. Particularly, Bayes' rule or Bayes' theorem is a means of computing a probability of predictive information when other certain probabilities of predictive information are known. Its formula is

28**as follows. P(A|B) = P(A) P(B|A) / P(B) This**

formula tells us that suppose there are two separate predictive information call 'A' and 'B'. What we want to find

25**is P(A|B)** when **P(A), P(B)**, and **P**(B|**A**) are known. **P**(A|**B) tells us**

10**how often** 'A' **happens given that** 'B' **happens. P(A)** tells us **how likely 'A' is on its**

own. P(B) tells us how likely 'B' is on its own, and P(B|A) tells us

20

10how often 'B' happens given that 'A' happens. In other words, P(A|B

), which is a probabilistic inference reflects the integration of P(A), P(B), and P(B|A), which are

15predictive information, in an approximately Bayesian optimal way. What can be the sources or the causes of predictive information

? Namely, the sources of these predictive information can be either the prior predictions— the priors,

20that are encoded in the generative model or the

likelihoods of the current potentially multi- sensory noisy information. If a belief is prior to an observation of a sensory input, then it is called a prior belief. Additionally, the likelihood is the sensory evidence (Figure 3). What does the Bayesian optimal integration mean? It is an optimal integration because it is based on their precision or uncertainty weights (Figure 3). That is, the predictive information that has more precision influences the integration more. In parallel, the more uncertain predictive information is, the less the influence is on integration (Figure 4). Nevertheless, optimality does not refer to accuracy (Tabor & Burr, 2019: 58). Thus, there may be a decoupling between a likelihood about incoming sensory information and a prior. Therefore, Bayesian optimal integration can result in a detachment from veridical sensory evidence. What is got after the Bayesian optimal integration, then? If a prior belief is Bayesian optimally integrated to either another prior belief or likelihood after observation of a new sensory data, then a new belief called a posterior belief is formed (Figure 4). Yet, 21 it is essential to note here what governs the Bayesian optimal integration. That is, the likelihood and the prior do not necessarily match. The mismatch between them governs the posterior formation through the Bayesian optimal integration. In other words, the Bayesian optimal integration is centered on the comparison and adjustment of the prior belief and the sensory input. However, why is the Bayesian optimal integration necessary, and why is it maintained over time? It is required for the formation of a belief that will be necessitated for the access to the source of a state. It is maintained in order to increase the degree of precision that is associated with a belief. That is, a belief is attached with a certain degree of precision. In other words, precision implies certainty that is associated with a belief. The precision of a belief, which is based on a sensory input, is tested against the

47precision of the sensory data. Further, the precision of the

sensation provides either evidence in favor of or evidence against the prior belief. What is the evidence against a prior belief in light of sensory data? It is the precision of

19prediction error, which is calculated via the difference between the precision of the

sensory data and the precision of the prior (Figure 3). That is, the precision of the prediction error provides how much evidence is given. In this respect, what governs the Bayesian optimal integration is the prediction error. Does this imply that the Bayesian optimal integration is biased?. Based on the relative

11precision of the sensory input and that of the prior

—i.e, based on the precision of the 22 prediction error, the posterior belief biases toward either of them. Suppose that the posterior belief is biased towards

9sensory evidence by either increasing the precision of sensory input and/or failing to attenuate it or decreasing the precision of the prior belief

(Figure 4-5). What is exactly the function of the prediction error? It is signaling learning, which occurs through the Bayesian optimal integration. How much learning is occurred is called the learning rate. It is calculated

11**by the ratio of the precision of the** prediction error **and the** precision of the **prior**

. Consider that the prior is constant, the learning rate relies on the precision of the sensory input. In this sense, the learning is open to change and the learning rate is variable. In parallel, a system can adapt to dynamically altering uncertain environment. However, how can the learning rate be increased allowing a system to adapt to its environment? It is ensured though a single imperative, which is the minimization of prediction error.

44**It is important to note that, the** prediction error **minimization**

should occur over the long-term average. To exemplify, if the precision of prediction error is too large, then the prediction error minimization will be excessive and the learning rate will be vast. Through prediction error minimization, a system adapts to its ever- changing and uncertain environment. What, more importantly, can a prediction error signal other than learning? It is false learning. That is, the predictive error minimization leads to maladaptation to an 23 environment. False learning or maladaptation to an environment is probable.

21**If the precision of the** sensory input **is overestimated or the precision of the prior is underestimated**, then **the**

precision of the prediction error will be huge. This situation yields that the posterior moves towards the sensory mean and away from prior mean. Consequently, this results in false belief or false inference. This culminates in a maladaptation of the system or the agent to the body or the environment. 2.2 The Predictive Coding Theory The predictive coding or Bayesian coding hypothesis is the first steps of the

24**predictive processing framework**. It depicts **that beliefs are** encoded in **the** form **of**

probabilitydensity distributions (Friston, 2010; Clark, 2013). Having said that probability density distributions encode uncertainty, encoding beliefs implies that the neural systems of biologically possible models take uncertainty into account fundamentally. Therefore, this hypothesis postulates that brain's learning can be cast in terms of statistics, in which uncertainty is transmitted within the neural networks (Rao & Ballard, 1999: 79). It suggests that, through this way, the neural networks optimize their connectivity and the dynamics among them in order

33**to maximize the evidence for its** generative **model of the**

environment (Hohwy, 2016: 259). 2.3 The Predictive Processing Framework The predictive processing framework casts Bayesian probabilistic inference pertaining to the prediction error minimization over the long-term average (Hohwy, 2013; Clark, 2013). That is, an internal generative model of a system or an agent 24 produces innumerable beliefs that are directed to capture the incoming sensory information. Then, what is a generative model? A hierarchical probabilistic internal generative model is

7**used to generate** an **expected** consequence **that may arise from hidden (latent)** state **of the** body or the **environment, and**, even, **in** the **absence of** the **external stimulation**

(Figure 6). It is

7**shaped over time to reflect** a precise representation **of**

the body and the environment. The prior beliefs are formed by the relatively higher mental states and carry weight with the relatively lower mental states, and that therefore, they are called top-down beliefs (Tabor & Burr, 2019: 55). The sensory data is created by the relatively lower mental states and carry weight with the relatively higher mental states. In parallel, they are also named bottom-up beliefs (Tabor & Burr, 2019: 55). In this regard, there is a hierarchy of beliefs within the model of the system. There are also bidirectional connections among them. That is, there are multi-level connections among beliefs. The internal generative model chooses the top-down belief that best matches with the sensory input thereby the prediction

49**error between the** prior belief **and** the **sensory data is**

minimized. After the countless trials of matching of the priors with the inputs, the internal generative model of the system promises the prediction error minimization over the long-term average. The reason lurking behind the process of prediction error minimization over the long- term average within the predictive processing framework is the hierarchical internal generative model's encoding of the probability distributions of the beliefs with uncertainty. The uncertainty encoded in the generative model is tackled with the precision-weighting process, where a belief associated with the highest precision is 25 weighted against the others. By the transmission of the difference between the belief with the highest precision and the actual sensory input

22**in the** form **of prediction error, the prediction error**

minimization occurs. The repetition of this process results in the prediction error minimization over the long-term average, in which the prediction error gets closer and closer to zero and the match gets closer and closer to exact match. 2.3.1 Perceptual Inference

36**Perception is a process of probabilistic** knowledge-driven **inference in the**

predictive processing framework (Clark, 2013: 2). It

30**arises as a result of** the **successful prediction-error minimization**

. To infer the source or the cause of an incoming sensory information or to perceive is perceptual inference (Clark, 2013: 6; Hohwy, 2013: 14). It refers to a mechanism that aims to meet the encoded sensory data with a prior belief of the hierarchical internal generative model of a system or an agent. That is, the prior is tested against the actual sensory input. An internal generative model encodes beliefs about the body and the environment as multiple top-down probability distributions

7**with differing degrees of** uncertainty. These **reflect a range of candidate** beliefs **about the** potential causes **of the** sensory state of **the** body or the **world**. Therefore, **the**

prior belief of the generative model may be from various spatial and temporal levels. 26 However, it is not exact issue of matching the prior directly with the sensory input. It is directed

17**to minimize the prediction error** that arises from **the** difference **between the** sensory information **and the**

prior over the long-term average (Clark, 2013: 7). Given that, it aims to use the prediction error

38**as a learning signal to** revise **the** system's **internal** generative **model**

of its body and environment, the perceptual prior beliefs refer to what the generative model has learned from its previous encounters with the source of the incoming sensory data (Clark, 2013: 7). When the prior beliefs are tested against the actual incoming sensory information, the evidence for the internal generative model is maximized for the accurate and precise beliefs. Further, the process of matching the prior with the sensory input involves computing various probability distributions of the sensory data (Clark, 2013: 7). The reason is that an inference may

16**be consistent with many** distinct **sets of causes**. They can be **distinguished only by their relative**

probabilities of occurrence. 2.3.2 Active Inference Action, within the predictive processing framework, is an inferential process (Clark, 2013: 6). The inference of an action by a system or an agent results in either an inferred outcome or predicted information through the action. In this regard, the inferred action is either exploratory or exploitative. That is, the system selects either an exploratory or exploitative optimal action policy to achieve what is estimated. The policy means a sequence of states leading to the concrete action or behavior. Under the selected policy, prediction errors may be induced because of the mismatch between

what is estimated and what is the current case. The system selectively 27 samples inputs to minimize the prediction errors under that action policy. To selectively sample, the system may alter its actions under that policy, thereby the sampled input may better reflect the predicted outcome or information. In parallel, there are two kinds of mechanisms described under

> 37**active inference (Friston, FitzGerald, Rigoli, Schwartenbeck, O'Doherty**, & Pezzulo, **2016**

: 864; Gadsby & Hohwy, 2019: 3). A particular mechanism of active inference is for utility. It is for reaping an outcome or reward. The other mechanism of active inference is for epistemic value. It is for reducing uncertainty about a system's internal generative model of its body or environment. Importantly, under active inference process, the systems cover the reduction of uncertainty within its model by means of fixing the model and changing its actions. 2.3.3 Active Learning An active system or agent minimizes prediction errors through either by carrying out actions to sample input that better captures what is inferred or by updating the parameters of the system's internal generative model to produce predictions that better reflect data (Friston et al., 2016: 864; Tabor & Burr, 2019: 55). The former alternative is introduced under active inference process. The latter is called active learning. The inference of an action policy under active learning is for mitigating uncertainty about the system's model. Instead of fixing the model and changing its actions, as

> 23**it is** 28 **the** case **for active inference, the model**

itself is updated in active learning. What updates the model is information in active learning process. In that sense, the inferred action policy is exploratory. Specifically, Bayesian optimal integration of the incoming information and the prior beliefs occurs over time to minimize the future prediction errors (Tabor & Burr, 2019: 56-7). That is, an active learner actively infers with increasing precision in future encounters (Clark, 2013: 10). 29 CHAPTER III WHY DOES PHYSIOLOGICALLY ACUTE PAIN OUTLAST ITS PURPOSES TO TRANSFORM INTO PATHOLOGICALLY CHRONIC PAIN AND WHY IS PATHOLOGICALLY CHRONIC PAIN ACCOMPANIED BY PAIN AVOIDANCE BEHAVIOR? Why physiologically acute pain outstays its functions to become pathologically chronic pain, and why pathologically chronic pain is accompanied by pain avoidance behavior remained elusive within the predictive processing framework. Essentially, in order to answer to these questions, I cast pathologically chronic pain and pain avoidance behavior as Bayesian probabilistic inference problems. Given that pain is a complex, convergent, and multidimensional experience, a Bayesian probabilistic model of pathologically chronic pain involves sensory, perceptual, affective, and motivational aspects. To date, the most researched feature of pathologically chronic pain within the predictive processing framework is established on perceptual inference. Following that, initially, I demonstrate what the perceptual inference account refers to regarding pathologically chronic pain. Up-to-date research holds that a complete understanding of pathologically chronic pain necessitates an explanation 30 of its motivational character, as well. However, when casting pathologically chronic pain and pain aversive behavior as Bayesian probabilistic inference problems, their motivational aspects call upon the explore-exploit dilemma and the

> 1**emergence of active inference and active learning**

. In parallel, I call attention to the different levels of uncertainty and their influence on the

> 1**emergence of active inference and active learning**

. Additionally, I show that different mechanisms are at work in gaining information and producing actions regarding pathologically chronic pain and pain avoidance behavior. Finally, I will propose that

> 1**active inference and active learning** lead **to the emergence of**

pain avoidance behavior and pathologically chronic pain, respectively. Therefore, section 1 describes the influence of perceptual inference over pain. Section 2 lays

> 16**out the key elements of the** explore-exploit dilemma. **Section 3**

elaborates the implications of this dilemma on the unfolding of pathologically chronic pain and pain aversive behavior that accompanies pathologically chronic pain. 3.1 The Perceptual Inference Account of Pathologically Chronic Pain Briefly, perceptual inference is a mechanism that functions in gaining information about the state that causes pain perception. What is inferred when pain is cast in terms of the perceptual inference is the cause of nociception. Perceptual inference is governed by the minimization of the mismatch between the encoded relative precisions of the incoming sensory data and the prior belief in

the predictive processing framework. In parallel, this principle applies to pain encapsulating physiological, pathological, and nociplastic pain resulting in nociceptive prediction error minimization. 31 The research on the sensory aspect of pain, particularly, nociception goes back a long way. Pain perceptions generally involve nociceptive aspect, although it is not necessary for all pains. For example, some patients with pathological pains arisen from spinal cord injury, or some patients with nociplastic pains resulted from fibromyalgia do not have nociception. Yet, in the case of physiological pain, there is generally nociception. One exception is congenital insensitivity to pain, which causes the lacks of nociceptors and, in parallel, the encoding of nociceptive input to the model of a system or an agent (Woolf, 2010: 3742). What governs the physiological nociception is the minimization of the mismatch between the relative precisions of the physiological noxious input and the prior belief in the generative model of a system or an agent. As to pathological pain, there is two directions to take. First, if there is not a nociceptive aspect of a particular pathological pain, then the perceptual inference account is insufficient to explain the pathological pain. Second, if there is a nociceptive character of a certain pathological pain, then the same principle—i.e., the

32**prediction error minimization**, applies. **However, this is the** tricky part. **The** reason is **that**

the perceptual inference mechanism points to the presence of an underlying deficit in precision optimization within pathological pain. Specifically, the prediction error is a function of the relative uncertainties of beliefs resulted from the actual nociceptive cause and the prior encounters with the nociceptive source. It should be minimized over the long-term average. It occurs through Bayesian optimal 32 integration. That is, Bayesian optimal integration implies the nociceptive prediction error minimization. However, it is biased. It allows that the posterior nociceptive belief, which is formed via integration of the sensory information and the prior belief, biases toward either of them. It may bias towards the nociceptive evidence by either

9**increasing the precision of** nociceptive information and/**or failing to attenuate it or decreasing the precision of the prior**

beliefs. Bayesian optimal integration indicates nociceptive learning. In other words, the nociceptive prediction error minimization means learning. If it occurs, then a system or an agent can adapt to the dynamically altering uncertain body and environment. However, false nociceptive learning may occur too. Having said that Bayesian optimal integration is biased, the precision of a nociceptive input may be overestimated and/or the precision of a prior may be underestimated or vice versa. This may result in the nociceptive posterior moves towards the sensory mean and away from prior mean. Through this, the predictive error minimization leads to maladaptation to the body or the environment or false learning, false belief, or false inference. That is to say that the nociceptive posterior belief may spend time deviating from the optimal nociceptive inference. This inference will manifest as more or less transitory false nociceptive inference or entrenched false nociceptive inference. As a result of the deviation from the optimal inference, it may fail to correct itself over time. This leads to a cascading and increasingly ensconced malfunctions. This refers to the pathological condition. As a result, this provides a ground for addressing how pathological pain perception is formed and maintained against counter perceptual evidencies. Given that the deviation from the optimal nociceptive inference requires time, the pathological pain 33 is maintained over time. The reason is that the reliance relatively more on nociceptive information leads to sampling and solving the uncertainties on the body and the environment more and for longer time. The deviation may entail time less than six months. In such a case, it may be referred as pathologically acute pain. However, if it endures more than six months or even a life time, then this may make it pathological chronic pain. Analogous to pathologically chronic pain perception, many psychopathological disorders are associated with inappropriate beliefs about precisions of the prior beliefs and sensory information. That is, they are linked with entrenched false inferences. To exemplify, autism spectrum disorder has been related with higher prior expectation for the sensory precision (

11**Van de Cruys, Evers, Van der Hallen, Van Eylen, Boets, de-Wit, & Wagemans, 2014**

). Particularly, a patient with autism spectrum disorder appeals relatively more to the senses than the priors with in the agent's hierarchical internal generative model's parameters (Hohwy, 2013: 161) Hallucinations in schizophrenia have been connected with higher prior expectations for the variations of the sensory input (Sterzer, Adams, Fletcher, Frith, Lawrie, Muckli, Petrovic, Uhlhaas, Voss, & Corlett, 2018). Delusions have been concomitant with false inference that is resulted from the reduction of the sensory precision in comparison with the prior precision (Adams, Brown, & Friston, 2014). Specifically, there is a heightened and continuous expectation for uncertain sensory data and increased and persistent reliance on the prior beliefs in both hallucinations in schizophrenia and delusions (Hohwy, 2013: 158). It is hypothesized that heightened chronic pain 34 expectation gives rise to heightened chronic pain perception (Hechler, Endres, & Thorwart, 2016). 3.2 Is Action Required for a Full-Fledged Account of Pathologically Chronic Pain? If a system or an agent has settled on a posterior perceptual or nociceptive inference resulted in pathologically chronic pain, then why

action should have a role in the system or the agent with pathologically chronic pain is a further inquiry. An answer may come from two different trajectories. If a pathologically chronic pain has a nociceptive aspect, then two supportive arguments in favor of action may be given. First, without action none of the beliefs of an agent can be favored strongly (Hohwy, 2013: 79). That is, action increases the precision and the accuracy of an inference encoded as a probability distribution. For example, suppose that one has happened to step on a lego piece in the middle of the night when she was trying to figure out the location of the light switch on the wall. The perceptual inference accounts for the noxious nociception caused by stepping on the Lego piece. She acts to minimize the following mismatch between the incoming sensory information—i.e., that there is something on the floor that may cause a damage on the body, and the prior inference—i.e., that the body integrity is intact. Many things can cause the exactly same inference. What causes this particular perception, which is a Lego piece, can be understood only by pulling her leg up, and turning her head down and gazing at the stuck piece on her foot. 35 Second, action is relatively more efficient than relying just on the perceptual inference (Hohwy, 2013: 80). In other words, to stay put for perceptions requires time, and it hereby is inefficient way to favor strongly an inference. For instance, one decided not take an action to turn the lights on and remained curious about what was the cause of noxious nociception perceived a couple of minutes ago in the middle of the midnight. Instead of carrying out an action to switch on the lights, she will wait the sunrise, thereby the sun light will fill the room and light the cause of nociception. This may take for hours. In contrast, switching on the lights takes just a couple of seconds. Therefore, active inference is relatively more efficient than the perceptual inference given a particular situation. However, the second trajectory comes from where there is no nociceptive information. That is, if there is not a nociceptive aspect of a pathologically chronic pain (along with nociplastic pain), then what makes the pain pathological and chronic (or nociplastic) necessitates an account of action. Hence, the perceptual inference account of pathologically chronic pain is insufficient for its complete understanding. It fails to account for its motivational aspect. What's more, the perceptual inference account of pain fails to account for the accompanying pain avoidance behavior. For instance, suppose one has a leg fracture due to falling on ice that may heal in three months. According to the perceptual inference, she will perceive a physiologically acute pain due to the fracture over this period of time. Especially, suppose that she perceives more pain when there is 36 pressure on the location of the fracture. Thus, she avoids leaning on her broken leg's side while sleeping to avert the perception of the physiologically acute pain. Suppose, further, that her perceptual inference deviated from its optimal precision and resulted in an entrenched pathologically chronic pain. Having said, she avoids to lean on her broken leg's side while sleeping to avert the perception of the pathologically chronic pain. Therefore, irrespective of whether this is a physiologically acute pain or a pathologically chronic pain, an account of action regarding pain is necessary. 3.3 The Explore-Exploit Dilemma: The Gap in the Pain Literature When pathologically chronic pain, which has a motivational aspect, and pain avoidance behavior are cast in terms of Bayesian probabilistic inference problems, they call for a deep scrutiny of action within the predictive processing framework. Bayesian probabilistic internal generative models are characterized by exploitative action or exploratory action strategies (Figure 7). In parallel, active inference and active learning lead to attenuation or uplift of the exploration and exploitation strategies as functions of prediction error minimization over the long-term average (Hohwy, 2013: 71; Marković , Goschke, &Kiebel, 2020: 3). Particularly, the equilibrium between exploration and exploitation is governed by the minimization of uncertainty by means of active inference and active learning (Seymour & Mancini, 2020: 5). However, balancing exploration and exploitation brings along the explore- exploit dilemma. It refers to knowing when to switch to exploitation of learned information, and to pause exploring for new information about an ever-changing and uncertain environment, and vice versa (Marković et al., 2020: 2). That is, if a certain 37 action yields prosperous surprise minimization, then how long the action should be prolonged culminates in the dilemma. Specifically, if the action perpetuated, then the system or agent would never know if the action is necessitated indefinitely within the environment, or if the cause of the action has otherwise ceased (Schwartenbeck, Passecker, Hauser, FitzGerald, Kronbichler & Friston, 2019: 1). Exploitative actions are outcome-driven actions (Friston et al., 2016: 863). That is, they are the best actions that result in the best outcomes based on the present beliefs about the environment (Schwartenbeck et al., 2019: 1). In this respect, they are pragmatic and susceptible to risks (Seymour & Mancini, 2020: 5). Contrarily, exploratory actions are information-driven actions (Friston et al., 2016: 863). In other words, they are the actions that yield information about whether

15**there are** any **better** action **whose outcome is partially or fully unknown**

at present (Schwartenbeck et al., 2019: 1). In this sense, exploratory actions are epistemic and susceptible to ambiguity (Friston et al., 2016: 863). There are two kinds of exploratory strategies: goal-directed and random exploration (Friston et al., 2016: 863). Goal-directed or directed exploration is motivated by uncertainty within a system's model of the environment based on either the uncertain mapping from a state to an outcome or an uncertain state (Schwartenbeck et al., 2019: 2). This entails that the system samples information that is held with the highest uncertainty (Schwartenbeck et al., 2019: 2). In addition to that, the goal-directed 38 exploration adds cost, noise, or bonus to policy that is arbitrarily chosen due to the highest uncertainty (Kakade & Dayan, 2002: 554). Here

1**it is important to note that** there are two **types of**

uncertainty or surprise, which are unexpected uncertainty and expected uncertainty (Schwartenbeck et al., 2019: 2). Unexpected uncertainty refers to ambiguity, whilst expected uncertainty refers to risk (Figure 8). In parallel, an exploitative policy is sensitive to expected uncertainty, whereas an exploratory policy is sensitive to unexpected uncertainty. Essentially, for a system, it is necessary to tackle with an ambiguity before tackling with a risk of a policy (Schwartenbeck et al., 2019: 2). There are, also, two types of goal-directed exploration: the hidden state exploration (Figure 7B), and the model parameter exploration (Figure 7C). Goal-directed ambiguity reduction relies on the mapping between the hidden state and the observation. That is, a system must infer both the action policy and the current hidden state that causes the observation. If the mapping from underlying a hidden state to an outcome is unambiguous, then the system can navigate to the outcome. This implies that the system can actively sample until it achieves the outcome, which has unambiguous mapping to the hidden state (Figure 9). In other words, the hidden state exploration can occur through active inference (Schwartenbeck et al., 2019: 2). Active inference ensures the hidden state exploration by driving a system to actively look for already learned or known salient 39 outcome that provides an inference of the hidden state unambiguously (Schwartenbeck et al., 2019: 5; Tabor & Burr, 2019: 56). For example, suppose that one flips a certain coin and always observes heads. Additionally, one has learned previously that a loaded coin always shows heads, and a normal coin shows a mixture of heads and tails when it is flipped a number of times. Thus, the mapping from the hidden state to the observation is unambiguous. In parallel, suppose that her inference is to observe heads if she flips it one more time. The hidden state that causes this observation and inference may result from that this certain coin is a loaded one. Yet, the hidden state can be just luck, as well. In this scenario her expected uncertainty is based on that this certain coin is loaded. Contrarily, her unexpected uncertainty is based on the idea that the observation of heads is due to mere luck. Her inference will be that if they rely on luck, then the coin will show tails at least one time; and if they are because of coin's being loaded, then the coin will show heads all the time. In order to minimize the unexpected uncertainty, her inferred policy will be to flip the coin multiple times. Suppose that she observes heads irrespective of the number of times flipping the coin. Thus, she infers that the coin is actually a loaded coin. However, if a system is ignorant about the mapping of its model, then the system acts in order to learn its model's previously unexplored contingencies. That is , if in a goal-directed exploration, a system needs to reduce not only the uncertainty

> 1**about the current hidden state**, but also **the** uncertainty of **the**

mapping between the hidden state and an outcome along with inferring the best action policy that is uncertain at present to achieve the uncertainty reduction, then it is model parameter exploration (Figure 40 9). It occurs through active learning (Schwartenbeck et al., 2019: 5). Active learning assures the model parameter exploration by compelling a system to actively try out

> 1**novel combinations of** the **hidden states and outcomes** in order **to** actively **learn about the** mappings, **in which** the **outcomes are**

guaranteed (Schwartenbeck et al, 2019: 7; Tabor & Burr, 2019: 55). To exemplify, suppose one wants to make soft chocolate chip cookies. Yet, suppose that she has a knowledge gap concerning the recipe of soft chocolate chip cookies. Particularly, she is uncertain about whether adding too much or not enough flour makes a chocolate chip cookie soft. Additionally, suppose that she is not certain concerning whether over-beating or under-beating the eggs produces soft chocolate chip cookies. Moreover, suppose that she has not learned whether she should melt the butter or she should not melt the butter for soft chocolate chip cookies. In this setting, her mapping from the hidden state, which is the recipe, to the observation, which is the softness of the chocolate chip cookies, is ambiguous. That is, these contingencies are associated with the highest uncertainties. To fill her knowledge gap— to learn and minimize the uncertainties, her inferred policy will be to actively try out novel combinations of the amounts of flour, egg-beating, and butter-melting. Additionally, for active learning to occur there must be

> 1**stable regularities or rules in** an environment **that can be learned**

(Figure 9). That is, active learning refers to being able

> 1**to carry information from one trial to the next. This is** provided **by the**

regularities or rules in an environment. Further, active learning occurs over time. In that sense, it is a slow way to reduce uncertainty. Contrarily,

> 1**active inference can** 41 **often be a faster way of reducing uncertainty**

(Schwartenbeck et al., 2019: 25). In the cases where active learning is broken and it is possible to calculate

uncertainty, active inference can reduce uncertainty instead of active learning. In contrast to goal-directed exploration, random or undirected exploration (Figure 7A) is directed to randomly sampling information regarding the altering and uncertain environment while diverging from the best action already learned given the current beliefs (Schwartenbeck et al., 2019: 1). This entails that a randomly exploratory action is not informed by a system's uncertainty regarding a hidden state or its mapping (Schwartenbeck et al., 2019: 8). Importantly, random exploration can allow a divergence from the currently best action policy whose outcome is fully and certainly known. It also occurs through active inference.

> 1**This implies that such** an action **will not decrease uncertainty per se but may cause accidental belief updating** or learning **due to random or stochastic selection of different policies**. In **this**

regard,

> 1**random exploration may** have **an adaptive function in the absence of goal-directed exploratory**

actions that may be a result of a system's inefficacy to calculate uncertainties—i.e., active inference and/or learning is broken (Schwartenbeck et al., 2019: 10, 25). Therefore, goal-directed exploration can refer to either exploring the hidden state that causes the outcome or exploring the parameterization of the system's model. Concurrently, gaining information and uncertainty minimization can be achieved by either

> 1**active inference** or **active learning. In** other words, **the** exploration **of the**

hidden 42 state is called active inference, whereas the exploration of the model parameterization is called active learning. Furthermore,

> 46**in the** lack **of goal-directed** exploration, **random exploration may**

result in adaptive learning. Importantly, inferences made through hidden state exploration by active inference and through model parameter exploration by active learning can either support or oppose each other (Schwartenbeck, 2019: 5). If there are regularities and/or rules within a system's environment that are stable enough in order to be learned through time by a system, then the hidden state exploration can be cast in terms of active learning. In this setting, the prediction made through hidden state and model parameter exploration boost each other (Schwartenbeck et al., 2019: 24). However, if the context changes randomly, then the hidden state exploration is cast in terms of active inference and may contradict with an inference made by active learning. That is, the minimization of surprise by means of model parameter exploration may produce an action that opposes the minimization of uncertainty through hidden state exploration when there is high ambiguity or novelty (Schwartenbeck et al., 2019: 25). Particularly, if an outcome is ambiguous due to the ambiguity in a system's mapping from a hidden state to its outcome, then the system infers that this is highly interesting and can be actively learned. Nevertheless, given that the outcome is ambiguous, it is highly aversive from the active inference perspective. For instance, suppose that one decided to watch a sci-fi movie she will enjoy, and what she got is The Matrix, The Matrix Reloaded, and The Matrix Revolutions. Suppose that she saw the Matrix and The Matrix Reloaded and really enjoyed the prequel. Additionally, suppose that she 43 has previously learned that the sequels are never better than the prequels. In this context, which movie should she choose? Given that she saw the first two movies, there is an unambiguous mapping from the hidden state—i.e., a movie, to the outcome—i.e., enjoyment and a prior belief that the prequels are the best. Her inferred action would be to choose The Matrix over The Matrix Reloaded since she would achieve the outcome through the hidden state exploration. Therefore, active inference results in that she should re-watch The Matrix. However, there is a novel, interesting, and informative option, which is The Matrix Revolutions. In parallel, in her mapping of the structure of the environment, there is a knowledge gap due to the ambiguous mapping that can be filled with model parameter exploration. Thus, active learning leads to that she should watch The Matrix Revolutions. 3.4 The Active Learning Account of Pathologically Chronic Pain and The Active Inference Account of Pain Avoidance Behavior So far, I have referred to the perceptual inference account of physiologically acute pain and pathologically chronic pain that was held until recently. After the progress in the predictive processing literature capturing the intertwinement of perceptual inference and active inference, I have touched on the latest well-establishment of the influence of action in the literature of pain. The up-to-date challenge is the position of the active learning within the framework and its contributory effect on pain. In connection with this, Tabor and Burr (2019) suggest that pathologically chronic pain is formed due to precision weighting of noxious information that eventually leads to the learned optimal precision weighting over time, and that informs a system's model 44 to explore or exploit its environment. Nevertheless, when the tables are turned, this paper does not elaborate on the offerings of the explore-exploit dilemma through

1**active inference and active learning to the** emergences **of**

persistent pain and pain avoidance. In order to pave the way for my research, I have pointed out to the exploration-exploitation dilemma within the predictive processing framework, as well. Thus, the question that I investigate here is exactly how active inference and active learning

29**play role in the** formation, **maintenance and** treatment **of** pathologically **chronic pain** and pain **avoidance behavior**

. The main motive lurking behind my current inquiry is that to track down the reason causing that physiologically acute pain outwears its purposes to convert into pathologically chronic pain. Additionally, to figure out the ground for the arise of concomitant pain avoidance is another motive of this analysis.

1**Active inference and active learning** lay out **a general** ground **for understanding** a system's **exploitative and exploratory**

actions (Schwartenbeck et al., 2019: 35). Following that,

1**active inference and active learning** mechanisms promise **a**

clarified

1**understanding of goal-directed cognitive deficits within the** scope **of**

psychopathological conditions (Schwartenbeck et al., 2019: 26). Further, the trade-off between exploitative actions and exploratory actions lies at the heart of pain, especially pathologically chronic pain and pain avoidance actions. Particularly, the interchange among hidden state exploration, model parameter exploration, random exploration, and exploitation is governed by their relative 45 precisions. Their relative certainties are products of the

45**prediction error minimization**, since **prediction error is a** function **of**

their uncertainties. Therefore, the trade-off between them is governed by minimization of uncertainties. In parallel, when pathologically chronic pain and pain avoidance behavior are casted as Bayesian probabilistic inference problems, they are guided by the minimization of uncertainties. Therefore, the minimization of uncertainty is closely linked with pathologically chronic pain and pain avoidance behavior. In parallel, the trade-off between hidden state exploration, model parameter exploration, random exploration, and exploitation is closely linked with pathologically chronic pain and pain avoidance actions. However, they may result in contrasting actions when an action policy is highly interesting and novel due to its high ambiguity and, at the same time, it is highly aversive because of the same reason—i.e., its ambiguity of the outcome. That is, if the outcomes of a policy are ambiguous respective of high ambiguity about the mapping between the policy and the outcome, then the policy is highly informative. However, if the system is certain regarding that the outcomes of the policy are ambiguous, then the same policy is highly aversive. Importantly, the ambiguity in the mapping of the system must be resolved before the resolution of the uncertainty about the outcomes. Hence, the uncertainty about the model parameterization modulates the effect of uncertainty regarding hidden states on action (Schwartenbeck et al., 2019: 25). 46 On top of these, I propose that, in the case of pathologically chronic pain, its formation and maintenance result from active learning, while accompanying pain avoidance behavior results from active inference. Consider the following argument. (i) Pathologically chronic pain is a pain experience that originates from a disease or an injury, and lasts for a long time irrespective of the endurance of what causes it. (Ass.) (ii) Pain avoidance behavior is the development and the maintenance of aversion to certain actions to refrain from inducing pain. (Ass.) (iii) Pathologically chronic pain and pain avoidance behavior involve goal-directed exploratory action strategies because the goal that directs them is to minimize unexpected uncertainty—i.e., ambiguity. (Ass.) (iv) A system or an agent with pathologically chronic pain has alterations, which work as stable regularities, within her mappings from the hidden states to their outcomes because of a past disease or injury. (Ass.) (v) If it is uncertain that the outcome of a goal-directed exploratory policy will result in pain due to high ambiguity regarding the agent's mapping between the hidden state to the outcome, then this policy is highly informative, interesting and novel—i.e., the model parameter exploration. (Ass.) (vi) Active learning is updating the parameters of a system's or an agent's generative model to produce inferences that better reflect the incoming information. (Ass.) 47 (vii) Therefore, pathologically chronic pain involves the model parameter exploration. The mapping of the system or the agent with pathologically chronic pain gets certain gradually through active learning. (i, iii, iv, v, vi) (viii) If it is uncertain that the outcome of a goal-directed

exploratory policy will result in pain, and the agent's mapping between the hidden state to the outcome is unambiguous; then this policy is highly aversive. (Ass.) (ix) Active inference is carrying out actions to sample input that better captures what is inferred either for epistemic purposes or achieving an outcome. (Ass.) (x) Therefore, pain avoidance behavior originates as the hidden state exploration through active inference. (ii, iii, viii, ix) (xi) Therefore, the same uncertainty in the outcomes of an action policy results in both the emergence of pathologically chronic pain and pain avoidance behavior. Pain avoidance behavior accompanies pathologically chronic pain. (v, vii, viii, x) (xii) Physiologically acute pain is a nociceptive or inflammatory experience that originates from a disease or an injury, and lasts for a short time with reference to the agent's gradual healing, which indicates no new stable regularities laid out biologically. (Ass.) (xiii) The action occurs as a result of physiologically acute pain involves exploitative action strategy. (Ass.) (xiv) If there is high ambiguity regarding the agent's mapping between the hidden state to the outcome in addition to that active inference is broken due to a disease 48 or an injury, which resulted in physiologically acute pain, then through active learning new biologically stable regularities are formed and physiologically acute pain turns into pathologically chronic pain. (Ass.) (xv) Therefore, the trade-off among the model parameter exploration, the hidden state exploration, and the exploitation is governed by the uncertainty minimization within the predictive processing framework. (vii, x, xiii, xiv) (xvi) Pathologically chronic pain and its accompanying pain avoidance behavior are psychopathological conditions. (Ass.) (xvii) Therefore,

> 1**active inference and active learning** mechanisms promise **a**

clarified

> 1**understanding of** the **goal-directed cognitive deficits within the** scope **of**

psychopathological conditions. (xii, xvi) 3.5 The Future Directions The thesis paves the way for three future directions in distinct disciplines such as philosophy, neuroscience, and medicine. First, given that pain is a complex experience, its modulators also enclose thought, beliefs and desires. They may have impacts on the emergence, maintenance, and management or treatment of pathologically chronic pain. Hence, the predictive processing framework is required to explain such propositional mental states (Williams, 2020). Second, although the computational approaches to cognition has a convincing advantage over the neuroscientific approaches to cognition, the neural underpinning 49 of the computational activities in the human brain is necessitated for a full-blown apprehension of cognition. In parallel, the brain

> 27**oscillations and** the **synchrony at different frequencies** may **provide** further **evidence on information flow across areas** of **the**

human brain, which underlies the computational processes. The neuroscientific approach to cognition combined with the prediction error framework hypothesizes that the information refers to the predictions and the prediction errors (Ploner, Sorg & Gross, 2017). Beta (12-30 Hz) frequency reflects the prior predictions and takes role in feedback signaling in the descending pathway of pain (Arnal & Giraund, 2012). Further, the prediction errors are reflected by gamma (30-100Hz) frequency and serves feedforward signaling in the ascending pathway of pain (

> 26**Pinheiro, Queirós, Montoya, Santos, Nascimento, Ito, Silva, Nunes Santos, Benevides, Miranda, Sá & Baptista, 2016**

). In the pathologically chronic pain cases, there is an abnormal increase in theta (4-8 Hz) frequency (Stern, Jeanmonod & Sarnthein, 2006; Sarnthein, Stern, Aufenberg, Rousson & Jeanmonod, 2006), however its role in the predictive processing framework has not been refined yet. It may be hypothesized that theta frequency refers to posterior inference concerning pathologically chronic pain. Third, having said that pain is fundamentally about action, the cognitive behavioral therapy (CBT) may promise noteworthy pain treatment methods. CBT is a kind of therapy that lies at the intersection of multiple disciplines such as psychology, psychiatry, pharmacology, and so forth (Tang, 2018). Its theoretical basis is on the 50 learning models such as the classical Pavlovian (habitual) conditioning, the operant (instrumental) conditioning, Rescorla-Wagner learning, associative learning, and so on (Tabor & Burr, 2019: 54). It adds the influence of beliefs and appraisals in the learning models. In addition, it recognize the effect of behavior on psychological responses. In parallel, the psychopathological conditions such as pathologically chronic pain can be treated by means of CBT. However, it necessitates that these learning models and active learning must find a middle ground. 51 CONCLUSION In this thesis, I disputed that the computational approaches like the predictive processing has a great advantage over the neuroscientific approaches

> 18**when it comes to** an efficient **understanding of the human**

brain. Peculiar as is pain, I held that pain worths to be studied philosophically because (i) it is not mechanistically explicable, (ii) it is not objectively identifiable, and (iii) it is not treatable but manageable according to what is currently known. Additionally, I made cases for evaluativism, imperativism, and psycho-functionalism regarding their explanatory power on pain. Yet, all three failed at different points. Further, I argued that the predictive processing framework holds out high hopes of refined comprehension of the goal-directed cognitive deficits within the scope of psychopathological conditions such as pathologically chronic pain and pain avoidance behavior. Particularly, I revolved around the questions (I) why physiologically acute pain overstays its protective function to become a pathologically chronic pain and (II) why pain avoidance behavior accompanies pathologically chronic pain. I made use of the explore-exploit dilemma to respond these inquiries. I inferred that (1) pathologically chronic pain comprises the model parameter exploration through active learning, (2) pain avoidance behavior involves the hidden state exploration through active inference, (3) physiologically acute pain results in exploitative action. I proposed that (a) the very same uncertainty in outcomes of an action strategy entails both pathologically chronic 52 pain and pain avoidance behavior, and (b) the high ambiguity in a system or an agent's internal mapping between hidden states to outcomes and the broken active inference because of a disease or an injury entail the transformation of physiologically acute pain to pathologically chronic pain. Thus, pain avoidance behavior accompanies pathologically chronic pain, and physiologically acute pain leaves its protective and adaptive purposes to turn into non-protective and maladaptive pathologically chronic pain. Moreover, the thesis has three future directions: (A)the predictive processing framework may bring forward an account for thoughts, beliefs, and desires, which modulate pathologically chronic pain, (B) the brain oscillations such as theta and the synchrony at different frequencies may require an investigation and may offer further evidence on information flow across areas of the human brain with pathologically chronic pain, (C) CBT may assure pathologically chronic pain treatment, if the learning models grounding CBT and active learning underpinning the predictive processing framework needs to settle a dispute. 53 REFERENCES Adams, R., Brown, H., & Friston, K. (2014). Bayesian inference, predictive coding and delusions. AVANT. The Journal Of The Philosophical-Interdisciplinary Vanguard, V(3), 51-88. Ali, S. A., Begum, T., & Reza, F. (2018). Hormonal Influences on Cognitive Function. The Malaysian Journal of Medical Sciences: MJMS, 25(4), 31–41. Appleton J. (2018). 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40**precision of the** actual sensorimotor **input** refers **to the precision of**

prediction error (PE). The precision of the prediction error is weighted and set off for the formation of a refined belief called a posterior belief. 64 Figure 4. The influence of precise source of information on posterior belief.

43**The relative precisions of the prior** belief **and the**

sensorimotor likelihood contribute to the precision of the posterior belief. If an inference is relatively more precise, then it has a greater impact on the formation of the posterior belief. The precision of an inference is shown as relatively more narrower probability density. For example, the precision of the sensorimotor likelihood remained as constant, if the precision of the prior belief is relatively higher than the precision of the sensorimotor likelihood, then the prior belief contributes more in the formation of the posterior belief, and the probability density of the posterior belief is drawn toward the prior belief (A). However, if the precision of the prior belief is relatively lower than the precision of the sensorimotor likelihood, then the the sensorimotor likelihood contributes more in the formation of the posterior belief, and the probability density of the posterior belief is drawn toward the sensorimotor likelihood (B). 65 Figure 5. The decoupling of the actual sensorimotor information from the subjective experience of a system or an agent. Within the predictive processing framework, there is a decoupling between an actual sensorimotor information and a prior belief of a system or an agent. Suppose that there is an actual threatening sensorimotor information in the environment. If there is a relatively precise prior belief that reflects the bodily integrity and safety of the system or the agent, then although there is a threatening current sensorimotor information, the posterior belief, influenced more by the prior belief, reflects the bodily integrity and safety (A). Contrarily, the prior belief is relatively less precise than the relative precision of the sensorimotor likelihood, then the posterior belief is relatively closer to the sensorimotor likelihood, and it reflects the threat towards the bodily integrity.

66 Figure 6. The hierarchical probabilistic internal generative model. It generates inferences that results from the hidden external states, and, even, in the absence of its external stimulation by the hidden states. It is formed over time to reflect a precise representation of the body and the environment. There is a hierarchy of inferences. The prior beliefs are generated by the relatively higher mental states. The sensorimotor likelihoods are created by the relatively lower mental states, and they carry weight towards the relatively higher mental states because of the mismatch between the sensorilikelihoods and the priors. 67 Figure 7. The classification of action strategies. Mainly, there are two types of action strategy: exploratory action strategy and exploitative action strategy. An exploratory action policy is information-driven. That is the role of an exploration is to gain information. There are two sub-types of exploration: random exploration and goal-directed exploration. A random exploratory action policy is to randomly sample information that is available in the body and the environment, which results in updating in the generative model of a system or an agent. It occurs through active inference (A). There are two kinds of goal-directed exploration: the hidden state exploration and the

1**model parameter exploration**. The **hidden state exploration is**

to gain information about the source of a sensorimotor information that causes an observation by means of active inference (B), whereas the model parameter exploration is to gaining information for generating the mapping from a hidden state to its observation through active learning (C). In contrast, an exploitative action policy is outcome-driven. That is, it occurs to achieve a certain observation via active inference (D). 68 Figure 8. The classification of uncertainty kinds. Mainly, there are two kinds of uncertainty: expected uncertainty and unexpected uncertainty. The expected uncertainty stands for risk, while the unexpected uncertainty refers to ambiguity. Exploitative action strategy is sensitive to risk (A). However, exploratory action strategy is sensitive to ambiguity (B). 69 Figure 9. The trade-off among the action strategies. Whether there is an ambiguity within a system or an agent's model's mapping from a hidden state to an observation or not, and whether the observation is ambiguous or not determine the system or the agent's action policy. Additionally, whether the ability of the system or the agent to make an active inference or to do active learning has influence over the trade-off among the action strategies. For instance, active learning may be broken by the lack of stable regularities in the body and the environment. As another example, active inference may be broken by the lack of activity in a certain body part. In parallel, stepping on lego pieces may need to the hidden state exploration for the observation of the lego pieces on the floor, while multiple sclerosis may need to the model parameter exploration for the precise representation of the current body form. 70