

Premise

Before turning to presenting the topic of our work and delving into the criticalities and opportunities of decision-making research, we believe that a brief introduction to the structure of the present work may help the reader orient amid the content of this dissertation, serving as a roadmap.

In Chapter I, we will start by mapping out the theoretical background of decision-making theories by outlining how theories have progressed from predominant economic and axiomatic models of decision to cross-sectional models incorporating psychological and neurobiological principles. The problematic nature of a pervasive consequence of this theoretical background will be discussed, by highlighting how abstract models have justified the practice of testing hypotheses within artificial and oversimplified environments while fundamentally failing to recognize that decisional rules evolved to support adaptation within naturalistic environments in the first place. Once identified the criticalities associated with disregarding the role of complex environments in shaping decision-making mechanisms, we will turn to investigate the interrelation between decision-making and some of the factors that are inextricably part of environmental complexity by studying their neurophysiological underpinnings; hence emotions and social behavior will be specifically addressed.

The investigation takes the form of three studies that, proceeding from the laboratory context to real-world applications, strive to widen the strictures of the experimental settings in an attempt to build toward more realistic models of decision-making. An effort is pursued across the research along two divergent directions, to reintroduce the environmental complexity into decision models on the one hand, while on the other hand aiming to extend the investigation of decision-making outside the lab, into the real world.

In the first study, described in Chapter II, the effect of emotional advertising on consumer response and purchase decisions is examined by the use of ecologically valid emotional stimuli through neurovascular, behavioral, and psychometric measures.

In Chapter III, the second study is presented, wherein the effect of social interaction on creative decision-making in the organizational setting is investigated within a naturalistic context through the assessment of central and autonomic electrophysiological measures and psychometric data.

Chapter IV is concerned with the last study, where the potential of a new neuroscience-based tool for the assessment of decisional efficacy at the workplace is tested, in an attempt to provide a basis for an ecologically valid and predictive measure of the construct.

Finally, in Chapter V, new roads to build models of decision-making that embrace the reality of environmental complexity and the decision-maker's biological constraints are discussed.

Chapter I – Theoretical background

“The world is a key for understanding the workings of the mind.”

Todd & Gigerenzer, 2007.

1.1 Complex world, complex decisions: From the roots towards a unitary vision

Decision-making stands out as possibly the most ubiquitous cognitive function that humans face in their everyday lives, presenting individuals with the constant challenge of selecting the most fitting course of action from a myriad of possibilities. At the same time, the decision-making process must be fast and flexible to allow individuals to stay on top of an ever-changing environment. Such contrasting duality of the decision-making fundamental requirements has long fascinated and divided scholars from different disciplines that have tried to build theoretical models of decision, and the debate still endures. In the present chapter, we will try to outline how far the debate has come in order to clarify where new disciplines can fit the discussion and how they can contribute to the development of realistic models of decision-making in mentioned complex environments.

In the 1930s, the advent of the neoclassical economic revolution consecrated the dominance of the normative approach in the field of decision-making. Led by economists, normative theories focused on abstracting the mathematical structure of decisions resulting from inferred preferences and observed behavior and generating models whose primary purpose was to predict choices based on a limited number of simple axioms (Samuelson, 1947). Central to this approach, to which *Expected Utility* (EU; Von Neumann & Morgenstern, 1947) and *Subjective Expected Utility* (SEU; Savage, 1954) belong, was the assumption that individuals are rational decision-makers, guided by instrumental rationality in their decisions and by the intent of maximizing the utility of the possible courses of action, “as if” an internal utility function would allow them to compare the value of different options and their multiple attributes on a common internal scale. Not secondary, the axioms of *transitivity*, *invariance*, and *dominance* of rational choice theories implied individuals to be consistent in their choices, unaffected by emotional factors and contextual variations. However, the power of formally concise and elegant mathematical models soon exposed its vulnerability when

empirical evidence began demonstrating that humans systematically violate all of the axioms of rational models.

Allais (1953) and Ellsberg (1961) paradoxes first, and Tversky and Kahneman's behavioral experiments later (Kahneman, 1979) set the stage for the development of descriptive theories. Evidence that individuals do not obey statistics, logic, and probability laws brought at the center of the investigation the observation of how individuals actually make decisions. A core frailty of neoclassical models was indeed they were essentially built on formal assumptions, rather than grounded on empirical data. The integration of psychological principles and behavioral data guided behavioral economists in an endeavor to devise empirically accurate psychophysical models of judgment and decision, that could provide a better predictive model of human choice than neoclassical theories. A central tenet of descriptive theories, such as *Prospect Theory* (Kahneman, 1979), indeed, consisted of formalizing a model of how human cognitive constraints and basic perceptual processes shape decision-making, wiping out altogether the idealized conception of full rationality. Acknowledging the human limited processing capacity, in fact, revealed the groundlessness of classical approaches that assumed individuals could perform multiple algorithmic computations to estimate utility, disposing of all necessary information in a -presumably- transparent environment. In this trail, the heuristics-and-biases research program came to be a core element of this approach, raising the evidence that human decision-making under incomplete information is guided by the systematic tendency to act illogically, namely, adopting cost-effective cognitive shortcuts that, although generally effective, predictably lead to systematic errors (Kahneman et al., 1982).

Before Tversky and Kahneman's fallacy-centric approach inextricably changed the perspective on heuristics in decision-making research, the theory of *Bounded Rationality* advanced by the father of heuristics, Simon (1956), initially proposed a functional perspective on heuristics. The concept, in fact, was born to identify simple but effective strategies that allow the decision-maker to reduce the computational effort required to make a decision while achieving a *satisfactory* outcome, in light of the constraints posed by human limited cognitive resources and by the environment, which would have made the computation of the optimal choice unattainable within

time and memory limits (in other words, determining a computationally intractable problem). Such *accuracy-effort trade-off* will necessarily bear less effort than the optimal solution, while yielding an outcome “*good enough*” to be valuable in the world where the decision-maker moves. Noteworthy, Simon introduces the structure of the environment as a crucial component to his theory, the absence of which would render the comprehension of human behavior impossible. Paraphrasing his famous metaphor, Simon conceived the relationship between the mind and the world akin to the blades of a pair of scissors, whose function cannot be understood by looking at one single blade at a time. Merely examining the cognitive blade in isolation fails to elucidate the mechanics of the decision-maker’s computation, unless cognition is considered in conjunction with the blade of environment. In fact, because cognition results from a process of adaptation to the environment, the latter is an essential requisite to achieve an understanding of the human mind.

Building on the intuitions of Simon - and of Brunswik before him - Gigerenzer formalized the theory of *Ecological Rationality* (Gigerenzer, 2000). In his endeavor of collocating bounded rationality in an adaptive environmental perspective, he overtly addressed the criticalities of many formal theories of decision-making that had previously aimed at deriving streamlined models of human choice by abstracting the behavior of the “*real decision-makers*” (Gigerenzer & Selten, 2002) from the environment, and testing predictions inside highly controlled experimental settings. In this perspective, the environment is rich in patterns of information that can be efficiently leveraged by “*computationally bounded minds*” to display heuristics that match as closely as possible the environmental structure. By exploiting the knowledge of the environmental structure, the decision-maker has learned a set of context-specific, fast, and frugal strategies (the heuristics) that only require minimal computational effort, which are nonetheless efficient, in that they allow for making accurate decisions and producing adaptive behavior (Gigerenzer, 2021; Gigerenzer & Gaissmaier, 2011; Todd & Gigerenzer, 2007, 2012). As a matter of fact, heuristics represent the tools at our disposal for survival and adaptation. In this light, it become apparent the elusive nature of testing decision-making theories inside artificial laboratory settings, where orthogonal experimental designs are purposely adopted to make the investigated variables unnaturally independent of each other (Rieskamp &

Reimer, 2007). Such artificially generated context does not mirror the statistical properties of the complex naturalistic environments to which decision-makers have adapted. It is therefore this mismatch that may lead to a short-circuiting wherein participants of experimental studies are induced to enact inefficient heuristics, leading to biased decisions and apparently irrational conducts. Importantly, a host of studies from different disciplines are beginning to highlight such short-circuiting (Fawcett et al., 2014; Mobbs et al., 2018; Schonberg et al., 2011). Hence, the way forward to make sense of systematic deviations from the expected rational behavior (from “the optimum”) involves conceiving biases as ecologically rational conducts, that humans have learned so to adapt to the real-world challenges. As ecologically rational behaviors are determined by the degree of the fit between the strategy adopted and the environmental structure (Gigerenzer & Selten, 2002), discounting the role of the environment from empirical tests raises questions about the generalizability of the results and, consequently, on the plausibility of the models derived so far (Fawcett et al., 2014).

1.2 Setting the stage for a unitary vision of decisions in complex environments

We would like to briefly emphasize here some core concepts of the theory of ecological rationality, the discussion of which we believe will be relevant in the following sections. First, it is important to note that the pattern of environmental information is not only physical in nature (e.g., the statistical pattern of occurrence of events in time and space), instead it encompasses also social and cultural sources. As individuals can shape environments through their social interactions, as well as through agent-environment co-adaptive loops, a special case of ecological rationality can be identified in *social rationality*. In this context, another class of tools can be displayed parallel to cognitive heuristics, particularly tuned to the facilitation of decision-making in social contexts: *social heuristics*, such as social norms, social imitation, and altruism can indeed support highly adaptive decisions within social exchanges. Other authors have suggested group heuristics that have been long pointed out as problematic biases may actually represent functional strategies that emerged because of their adaptive role in preventing obstacles in group coordination and motivation, favouring the

group adaptation and selection in face of the world's complexities (Tindale & Kameda, 2017). Secondly, in a related vein, emotions too represent a category of domain-specific tools that prove particularly beneficial in addressing adaptive challenges, encompassing areas like mate selection, social interaction, and food choice. Notably, prior theories of decision-making have systematically disregarded the role of emotions. Even when acknowledged, as seen in prospect theory, they have been regarded merely as a fast component contributing to irrational biases and hindering decision-making process, as exemplified by the framing effect (Kahneman, 2011). Conversely, social and emotional competences are here to be considered boundedly rational strategies that come to the aid of rational conducts. Third, the theory of ecological rationality focuses on cognitive abilities rather than "cognitive limitations". Beyond the fact that this terminology is refused in as much as it is rooted in the unrealistic comparison with full rationality, it furthermore sounds inappropriate considering that a staple of the theory posits that if a heuristic matches the environment properties, the heuristic can paradoxically generate more accurate predictions than computational models. Studies have provided supporting evidence showing that, in unpredictable, complex environments, decision heuristics that are based on one-reason rules outperform predictions of statistical models such as machine-learning and neural networks (Chater et al., 2003). Finally, and perhaps most importantly, at the core of ecological rationality stands the principle of psychological and biological plausibility of the "adaptive toolbox" (i.e., the system of heuristics in our mind). The theory is indeed aimed at creating computational models of heuristics by drawing from the biological, behavioral, and psychological capabilities realistically possessed by humans, acknowledging a role also for the neural mechanisms linking decision-making and bodily perception (Gigerenzer, 2007).

In light of these premises, it is apparent that ecological rationality reveals several contact points with other disciplines concerned with unravelling decision-making mechanisms. Among biological and ethological sciences, a growing body of studies have supported the notion that decision rules evolved to be adaptive to conditions that are naturally subject to stochastic fluctuations and are correlated in time and space (Fawcett et al., 2014; McNamara & Houston, 2009), highlighting that abstract models of decision that do not take into account structural properties of the environment may

not fit appropriately in the complex real-world contexts (Fawcett et al., 2013, 2014; Mobbs et al., 2018). On the other hand, considering the acknowledgment of the role of emotion and social components in decision and judgment, significant connections emerge with affective neuroscience, embodied emotion, and neuroeconomics (Xu et al., 2020), whereas recognizing the adaptive value of fast and computationally cost-effective strategies points at evident similarities with computational neuroscience (Koechlin, 2014). Therefore, we believe ecological rationality offers a meaningful theoretical precursor that may guide and propel a unified vision of decision-making, in the conviction that an interdisciplinary integrated approach may help gain a more complete understanding of how decision-making actually unfolds in real-world complex environments.

1.3 Towards an integrated rationality: affect and social interactions in decision-making

Much of the decisions we deal with in our everyday lives are intrinsically tied to the highly complex social environments we inhabit and closely intertwined with emotional factors. Nonetheless, the predominant theories of decision have long disregarded or pathologized affective components, until the advent of neuroscience. In the last three decades, technological advances in neuroscientific techniques have allowed to develop the knowledge of the neurophysiological correlates of decision-making, significantly contributing to uncover especially the “submerged world” (Tolone, 2021) of the unconscious processes engaged by decision-making, addressing first and foremost emotions. The groundbreaking Somatic Markers Hypothesis (SMH; Damasio, 1994) has greatly contributed to this process. Based on the neuroscientific evidence collected throughout decades of research, Damasio came to posit that emotions are to be conceived as an essential part of the reasoning process, hence, extruding the investigation of emotions and neurophysiological correlates from the formalization of a theory of rational decision would make such theory null and inadequate. In fact, decision-making is significantly influenced by chains of bio-regulatory processes occurring in the body and in neural structures as a result of emotions and feelings (Bechara & Damasio, 2005). In essence, past experience with a class of emotional stimuli is stored in the ventromedial prefrontal cortex (VMPFC) in the shape of learnt associations between the stimulus (the *primary inducer*) and the bio-regulatory

somatic and emotional states that were associated in the first place with the stimulus. Whenever a situation that shares common aspects with the primary inducer (a *secondary inducer*, such as memories or thoughts about the primary inducer) will be experienced, the VMPFC will prompt the re-activation of the learnt somatic patterns in brainstem nuclei and in somatosensory cortices, inducing a bodily activation fainter but similar to the one belonging to the primary inducer. Bodily information will then be conveyed back - primarily through the vagal nerve - to higher-order neural cortices, such as the dorsolateral PFC, a fundamental substrate for executive control and working memory, affecting this way decision-making (Poppa & Bechara, 2018). In decision-making, thus, new situations can trigger secondary emotions which, based on learnt associations, can re-activate somatic markers. The latter will be experienced as *gut feelings*, which may be consciously or unconsciously reinterpreted as anticipatory positive or negative feelings that can accordingly predispose the decision-maker towards alternative choices. Bodily markers, thus, precede any cognitive cost/benefit analysis and intervene by biasing the decisional process according to gut feelings about anticipated outcomes.

For the sake of the present research, two considerations appear of particular importance, as highlight relevant connections with the concept of ecological rationality. First, the SMH openly acknowledges the pivotal role of environment. As the formation of somatic markers depends on past experience, the associations we learn and store in VMPFC are rooted in the environment we have experienced. This also acknowledges the inevitable social and cultural nature of the environment (Damasio, 1994; Tolone, 2021), and implies that the adequacy of the ever-expanding repertoire of adaptive strategies one can dispose of in decision-making is deeply interwoven with whether the social environment where future decisions will take place match the structure of the environment where those strategies were primarily experienced.

Secondly, somatic markers are what give rise to intuition. When operating at the unconscious level, they may facilitate decision-making by what Damasio calls a “preselection” mechanism (Damasio, 1994). Decision-making in complex decisional problems can become faster and less costly if the range of options is narrowed down by removing early on options that elicit negative gut

feelings or endorsing the ones associated with positive anticipatory feelings through intuitive wisdom. A concept that closely resembles that of emotional heuristics proposed by Gigerenzer (Gigerenzer & Selten, 2002). Intuition, in fact, enables the resolution of complex, time-demanding problems under uncertain environments. As evidence thereof, numerous studies conducted on patients with neurological impairment to core regions involved in the generation of somatic markers (such as the VMPFC and the amygdala) have revealed a systematic pattern of deficits that severely hinder the patients' decisional abilities (Bechara, 2000, 2004; Bechara et al., 1996, 1999; Damasio, 1990; see also Bechara & Damasio, 2005; Reimann & Bechara, 2010 for a review). A reduction of emotional reactivity was in fact consistently associated with reduced or inexistent anticipatory autonomic activity (the somatic marker). This pattern was systematically observed in concomitance with the inability to anticipate negative outcomes, the incapacity to learn from past mistaken choices, a short-sighted perspective in decisions, and increased rigidity of the decision criterion, signalling altogether the impossibility of acquiring relevant information from the environment and deploying it at the service of decision-making. Paradoxically, when the access to emotional (and somatic) information was hampered, and patients could only rely on cognition, their decisions turned out fallacious and less rational. Therefore, "rational", adaptive, decisions are only possible if reason and intuition act synergistically: to recover a full, *integrated*, rationality, as other authors have suggested (Tolone, 2021), the decision-maker's cognition and emotion need to be reconciled, as well as her mind and body. The decision-maker needs to be recognized as an actor embedded within a circular flow with the environment, of which her body is a fundamental mediator, instrumental to ensure a state of homeostatic balance and, ultimately, survival.

In light of their commonalities, SMH has been said to offer empirical evidence in support of ecological rationality and it has therefore been proposed as a functional neurobiological framework to bridge the principles of ecological rationality to neuroeconomics (Xu et al., 2020).

After the SMH opened the gates of decision-making to emotion through neurobiological supporting evidence, the study of the role of affect in human decision has experienced a surge in neuroscience research. A fundamental distinction has been observed in the way incidental affective

components (i.e., extrinsic to the decision task, such as stress and mood) and integral emotions (i.e., elicited by the option itself, contributing to the computation of its subjective value) differentially affect a variety of decision problems, spanning from risky decisions, decision under uncertainty, and intertemporal choice (Lerner et al., 2015; Phelps et al., 2014). A complex picture has emerged from the first years of research in affective neuroscience, highlighting that a host of neural areas are implicated in emotional processes occurring during decision-making, and that their activity can significantly vary according to different types of decision. Although the understanding of how different neural systems involved in emotional responses are engaged during decision-making is still limited as the field abounds with mixed findings, some cornerstones have been identified so far. For instance, the amygdala is a subcortical region whose vital role in associative learning of aversive stimuli – or more in general, unexpected cues - and value of the outcomes through arousal has been well documented (Li et al., 2011; Phelps & LeDoux, 2005). The striatum was shown to be crucially involved in motivation and, in virtue of its afferent connections from the amygdala, can integrate motivation and action values, contributing to loss aversion responses and prediction errors (Daw et al., 2011; McClure et al., 2003; Roesch et al., 2012). Afferences from the amygdala also reach the orbitofrontal cortex (OFC) and the VMPFC, which have been implicated in affective processes as well as in the computation of reward subjective value (Levy & Glimcher, 2012; Rudebeck et al., 2013). Furthermore, activity of the anterior insula was consistently associated to unfair, risky or ambiguous choices, suggesting its implication in eliciting negative emotions, such as disgust, stress, and anger to signal aversive outcomes (Clark et al., 2008; Kuhnen & Knutson, 2005; Naqvi et al., 2006; Weller et al., 2009).

Moreover, advances in this research strand paved the way to the investigation of the neural underpinnings of social preferences in economic decisions, giving rise to the field of social neuroeconomics (Fehr & Camerer, 2007). The application of neuroscientific techniques to social decisions has provided a valuable contribution to the *Game Theory* approach (Von Neumann & Morgenstern, 1947), showing the potential to disentangle the neural mechanisms that support social decision-making through sophisticated experiments that strive to mimic social exchange in the

laboratory context. This way, the range of decision problems under the lens of the investigation has expanded so to include the study of trust-related decisions, altruistic choices, fairness and inequity, negotiation, peer pressure, and decision under competition or cooperation (Rilling & Sanfey, 2011; Somerville et al., 2019; Tzieropoulos, 2013; Van Hoorn et al., 2017). In this context, substantial effort was dedicated to target the neural structures associated with social behavior and Theory of Mind, such as the Superior Temporal Sulcus, the Temporoparietal Junction, or the dorsomedial PFC, as it was shown that the social factors can importantly sway decision behaviors (Behrens et al., 2008; Bitsch et al., 2018; Strombach et al., 2015). As in fact it will appear clear, the exquisitely human ability to understand and anticipate other people's intentions and emotions (in one word, mentalization) might have evolved to grant evident benefits in economic decisions (Rilling & Sanfey, 2011).

A comprehensive review of all the neural circuits that have been implicated so far in mediating the contribution of emotional and social factors in decision-making is beyond the scope of this introduction and could be hardly accomplished in such a limited space. For the sake of brevity, we have chosen to present only some of the primary findings that have garnered wider consensus among the scientific community. Nonetheless, even from this short illustrative selection, a complex plurality of intertwined and interacting neural systems undoubtedly emerges. It should be underlined that these findings conflict with the long-predominating perspective of dual-process theories, which have conceived emotion and cognition as conflicting and incompatible modalities (Kahneman, 2011), paralleled by the distinction between automatic and controlled processes in neuroscience (Posner and Snyder, 1975; Schneider & Shiffrin, 1977). Up to date, a growing body of evidence has ruled out a clear-cut segregation between emotional and cognitive systems. Once identified with well-separated neural areas, respectively encompassing the limbic system for emotion, and predominantly the prefrontal cortex for cognition, research has now shown that even those neural networks that were thought of as involved in purely emotional processes eventually showed to play a role also in cognitive functions (e.g., although being part of the limbic system, the hippocampus is causally involved in memory functions; LeDoux, 2000) and vice versa. A more appropriate understanding of

the relationship between emotion and cognition in decision-making thus needs to be achieved by acknowledging the modulatory nature of the interaction between multiple neural networks, synergistically orchestrating the effect of socio-affective components on deliberate decision-making (Brocas & Carrillo, 2014; Grayot, 2020).

1.4 Neuroeconomics: economic decisions grounded on neurobiology

Neuroeconomics is a recent research field at the intersection of economics, psychology, and cognitive neuroscience that aims at deriving realistic models of economic decision-making by investigating the underlying neural mechanisms (Sanfey et al., 2006). Its origin represented a natural development of those behavioral economic models that began theorizing algorithms of human information processing and decision-making based on the popular brain-computer analogy, inasmuch as advancements in neuroscientific methods could then offer an empirical verification of the speculated algorithms (Glimcher et al., 2009).

Neuroeconomics has inherited much of the theoretical framework from behavioral economics. However, as research has shown that the rational *optimum* is unrealistic and unattainable both at a neural and behavioral level, neuroeconomics draws upon the theory of behavioral economics to build an abstract benchmark of optimality against which to compare actual behavior, rather than assuming optimality as the expected rational behavior. Observing systematic deviations from the benchmark, indeed, can generate insights on how the brain actually works, and can help hypothesis testing of new theories of economic decision grounded on neurobiological data (Sanfey et al., 2006). By relying on the unified vision proposed by economics, indeed, this new-born discipline has significantly advanced knowledge regarding how the brain computes core economic properties of the options, such as probability, value, and utility (Levy & Glimcher, 2016; Levy & Glimcher, 2011, 2012; McClure et al., 2004a; Padoa-Schioppa, 2011; Padoa-Schioppa & Assad, 2006; Platt & Glimcher, 1999).

At the same time, and most importantly, neuroeconomics draws upon a fundamental axiom of neuroscience, that is, it assumes a multiplicity of neural systems coexist and interplay through connectivity-based modulatory interactions (Dennison et al., 2022; Grayot, 2020; Hare et al., 2009; Kable & Glimcher, 2007; Sanfey et al., 2006; Serra, 2021). Acknowledging the plurality of the systems that contribute to the decisional process has led neuroeconomics to deeply intertwine with other two sub-fields of cognitive neuroscience beyond decision neuroscience, namely, affective and social neuroscience (Camerer et al., 2005; Fehr & Camerer, 2007; Serra, 2021). Thanks to this interdisciplinary cross-contamination, neuroeconomics has set the stage for the uncovering of the manifold effects of emotions in economic decision-making (Xu et al., 2020). For instance, recent research has applied the SMH framework to explore the effect of emotional and interoceptive signals on individual and social economic decision (Dunn et al., 2012; Lenggenhager et al., 2013; Lo & Repin, 2002; Sharika et al., 2023; Shiv et al., 2005; Sokol-Hessner et al., 2015).

Crucially, research in this field has led to a ground-breaking discovery concerning the existence of a unitary system in the brain that constitutes the neural substrate of a common neural “currency” (Montague & Berns, 2002). This mechanism would serve as an internal scale on which the value of different rewards can be universally compared, regardless being different in nature, not much dissimilar from that internal common scale hypothesized by rational theories of decision (Samuelson, 1947). However, this mechanism appears to be affective in nature. A growing body of studies have in fact progressively revealed that a specific subregion approximately overlapping with the VMPFC and the OFC is consistently activated by a variety of reward types, whether primary (e.g., food or money) or secondary (e.g., emotional or hedonic value), concrete or abstract, self-directed or altruistic. What is more, the investigated area has shown to be indiscriminately implied in decision under uncertainty, risk, and even counter-factual decisions, while its activation to be dose-dependent to the desirability of the reward (Bartra et al., 2013; Clithero & Rangel, 2014; Levy & Glimcher, 2012). Far from being the substrate of a rational utility quantification system, such mechanism appears to be informed by different neural pathways implicated in the elaboration of distinct aspects of reward, including emotional, social, and mentalizing systems (Fellows, 2004;

Levy & Glimcher, 2016). Indeed, this area possibly represents a crucial hub implicated in the integration of two types of signals: higher-order cognitive components on one hand, and lower-order signals implied in basic forms of affect and physiological regulation on the other (Roy et al., 2012). By integrating these two facets of a reward, this unique subregion serves the function of computing the affective meaning of a situation and eventually translates adaptively relevant cognitive information into affective behavioral and psychophysiological responses (Levy & Glimcher, 2016). Neuroeconomics has thus provided neurobiological evidence that the computation of the value signal is intrinsically affective, and that observed decision behavior may be the outcome of a mechanism of maximization of this computed value.

By incorporating human biological constraints into economic models, neuroeconomics has not only shown the inadequacy of the standard theories of economic choice, but it has also significantly pushed forward the understanding of the idiosyncrasies of economic behavior and its underlying reasons. On the one hand, confirmation has been provided to some of the psychological principles proposed by previous behavioral models to be responsible for the observed apparently irrational conducts. Prospect theory's loss aversion is a good example of this, wherein a host of neuroscientific studies have now observed loss aversion and its neural underpinnings (Tom et al., 2007). More importantly, neuroeconomics has provided solid explanations and objective rationale for economic behavior, by uncovering neurobiological mechanisms that make sense of "irrational" behaviors both in individual and social decisions according to an evolutionarily adaptive and emotional form of "utility function". The potential of neuroeconomics lays indeed in turning from "as if" abstract models, that are agnostic about what happens inside the "black box", to the investigation of the physicality and the mechanics of the neural systems that actually support the decision-making process (Levy & Glimcher, 2016), addressing both Marr's algorithmic and implementational level of analysis to set the stage for the computational level (Marr, 1982).

Moreover, neuroeconomics evidently recognizes that decision-making is intrinsically bound to emotional and social factors that arise in our everyday life decision problems. By doing so, an apparently trivial but fundamental property of the human neural system is acknowledged and taken

into account, namely, context-sensitivity (Pessoa, 2017). Hence, the success of endeavors aimed at a realistic understanding of decision-making hinges significantly on the acknowledgment that decision processes are intricately constrained by the environment surrounding us. Building upon this notion, neuroeconomics is in fact experiencing a constant explosion of sub-fields of research that are concerned with investigating decision-making within applicational contexts, such as consumer neuroscience, financial decision-making, and organizational neuroscience. Therefore, grounding the study of economic decision into the biological constraints of the decision-maker and into the properties of the environment that the decision-maker inhabits shows potential for building more realistic and accurate predictive models of decision-making (Serra, 2021).

1.5 A methodological framework for decisions in complex environments

As we have highlighted in the previous sections of this chapter, realistic accounts of decision-making within complex environments cannot proceed without bringing under the investigative lens the emotional and social elements that are intrinsically part of those environments.

Emotional and social phenomena have been studied for decades by means of verbal and self-report psychometric tools that build on introspection. However, in relatively recent times, a debate has arisen among the scientific community concerning the adequacy of verbal tools to handle the investigation of affective and automatic processes (Bagozzi et al., 1991; Camerer et al., 2005; McClure et al., 2004b). Much of human behavior, in fact, is driven by the multi-modulatory interplay of conscious, deliberative processes and unconscious, automatic ones, so that even processes that were long thought to be steered by pure cognition (such as decision-making) are actually the result of unconscious processes to some extent (Wolford et al., 2000). Therefore, by relying on traditional tools that require participants to verbalize their thoughts through introspection, the contribution of the numerous processes that occur outside of awareness would be overlooked - or heavily biased at the very least. Furthermore, regarding those emotional processes that face the surface of awareness to a sufficient extent to be inquired upon, the request to put those emotional experiences into words

would actually results in a measure of the cognitive appraisal of those emotional components (Levine et al., 2018).

On the other hand, research abounds of evidence that self-reports are subject to a host of response biases. Social desirability bias (Grimm, 2010; Tracey, 2016; van de Mortel, 2008) may significantly sway the accuracy of self-reported traits or behaviors, especially when socially sensitive topics are addressed by the research. Confirmation bias (Peters, 2022; Schumm, 2021) and constraints of human memory capacity (Levine et al., 2018; Van Den Bergh & Walentynowicz, 2016) can also introduce important limitations in self-report measures, just to cite a few examples. In regard to the latter, the very nature of self-report instruments makes them unsuitable for real-time administration during experimental tasks – for instance, a decision task requiring social interaction. Confining self-reports to an offline administration (i.e., at the end of the experimental paradigm) creates room where memory biases can insinuate.

Building on these premises, we believe that a more fruitful approach to the study of emotional and social components interacting with decision-making should lean on the contribution of the methodologies belonging to cognitive neuroscience.

The birth of cognitive neuroscience was made possible by the impressive technological advances of neuroscientific methods in the late 1970s, which have progressively enabled unparalleled access to neural structures. At the core of cognitive neuroscience stands a multilevel and multimethodological approach, which allows garnering insights from the convergence of neurophysiological and behavioural data upon which psychological inferences can be drawn, with the purpose of building psychological theories of the cognitive processes by unveiling their neurobiological underpinnings (Ochsner & Kosslyn, 2013). To pursue this goal, cognitive neuroscience's approach involves devising experimentally sound behavioral tasks during which neurophysiological measures are collected on the experimental subjects to perform hypothesis testing. A variety of neurophysiological methods have been developed and fruitfully applied so far. Among them, one class of methods is aimed at investigating the activity of the central nervous system (CNS). Non-invasive measurement techniques encompass electroencephalography (EEG),

magnetoencephalography (MEG), functional near-infrared spectroscopy (fNIRS), functional magnetic resonance imaging (fMRI), single-photon emission computed tomography (SPECT), and positron emission tomography (PET), while single-unit recording is an invasive (hence, infrequent) technique. Non-invasive brain stimulation techniques also belong to the toolkit of cognitive neuroscience, such as transcranial magnetic stimulation (TMS) and transcranial direct current stimulation (tDCS). Alongside, another heterogeneous class of tools is directed at providing measures of the peripheral nervous system (PNS), which encompasses skin conductance response (SCR), cardiovascular measures (e.g., electrocardiography (ECG), photoplethysmography), electromyography (EMG), pneumography, eye tracking, and pupillometry, to cite a few examples.

Because each one of the mentioned methods presents different degrees of spatio-temporal resolution and specific methodological constraints, the suitability of each technique is to be considered contingent upon the experimental design and research question. In the context of the present research, fNIRS, EEG, SCR, and cardiovascular measures emerged as the most suitable methods to investigate our research questions, hence we will here provide a brief overview of each one.

1.5.1 Neuroimaging and electrophysiology for the central nervous system

Functional near-infrared spectroscopy (fNIRS)

Functional Near-Infrared Spectroscopy (fNIRS) is a non-invasive optical neuroimaging technique that relies on measurement of changes in blood oxygenation and hemodynamic response in the brain to infer variations in neural activity. This technology has revealed particularly fruitful for studying brain function in a range of applications, including neurodevelopmental research, clinical studies, and cognitive neuroscience (Balconi et al., 2015; Ehlis et al., 2014; Lloyd-Fox et al., 2010). This technique utilizes near-infrared light (NIR) in the range of 700 to 2500 nanometers (Hoshi, 2016) to penetrate the scalp and skull, reaching the superficial layers of brain tissue by taking advantage of the transparency property of the skin and bones to NIR light. Latest studies generally

employ multichannel headsets involving sets of paired emitters – the optical fibers injecting the light into the scalp - and detectors – the fibers receiving the scattered light – placed at a distance of 30-35 mm in adult subjects (Pinti et al., 2020). The portion of brain tissue in the mid-point between the source and the detector thus forms a “channel”, and represents the cortical area investigated by the NIR light. In fact, the brain tissue, which is anisotropic and inhomogeneous, affects the NIR light through processes of absorption and scattering (Delpy & Cope, 1997). The NIR photons injected into the brain are absorbed to different degrees by distinct substances in the brain tissue - such as water, lipids, and hemoglobin – according to their specific molecular properties (chromophoricity). Crucially, oxygenated (O_2Hb) and deoxygenated (Hb) forms of hemoglobin show distinct absorption coefficients. As an increase of neural activity in brain regions determines an enhanced metabolic activity and a variation in the cerebral hemodynamic flow, an increase in O_2Hb and a decrease in Hb concentrations is observed. Hence, these hemodynamic variations are measured by fNIRS through alterations in light attenuation that reached the detector, allowing to derive insights into variation of neural activity in specific areas (for a comprehensive discussion see Hoshi, 2016; Pinti et al., 2020).

Notably, good spatial and reasonable temporal resolution, together with the portability, safety, and tolerance to motor artifacts demonstrated by fNIRS have led the tool to be acknowledged as suitable for a range of experimental settings, and have contributed to its growing popularity in the field of neuroscience. With technological advances leading to smaller and portable devices, the number of studies adopting wearable fNIRS setups within naturalistic settings in search of higher ecological validity has been on the rise (Herold et al., 2017; Quaresima & Ferrari, 2019).

Electroencephalography (EEG)

In the field of electrophysiology, electroencephalography is by far the most widely used method to record brain electrical activity non-invasively. Invented by Hans Berger in 1924 (Berger, 1929), EEG has been employed across more than one century of clinical practice and experimental research and has brought invaluable contribution to the study of the electrophysiological dynamics

of the brain by unravelling the underlying neural mechanisms of human cognition and psychopathology (Cohen, 2017). EEG, in fact, captures electrical potentials generated by the synchronized activity of vast neural networks resulting from ionic currents in the brain.

To do so, most EEG studies place electrically conductive electrodes on the scalp surface via EEG caps to record variations in electrical potential - although also more invasive setups exist, where electrodes are placed intracranially. To ensure consistent positioning of the electrodes on identifiable brain regions, EEG caps are usually conformed to the 10-20 or 5-10 International System (Jasper, 1958).

EEG detects synchronous changes in the membrane potentials of the apical dendrites of large portions of cortical neurons (Ruff & Huettel, 2014). Synaptic excitation of the apical dendrites result in ionic currents across the membrane, and the spatial and temporal integration of synaptic transmission in the dendrites can lead to the formation of electromagnetic dipoles and magnetic fields within the cell (Müller-Putz, 2020). If large networks of neighboring neurons receive synchronous synaptic transmissions, the resulting electrical field generated by the summation of their activity can spread across the brain over long distances, and can potentially be detected at the scalp surface. Importantly, EEG signals mainly reflect post-synaptic potentials of collective populations of neurons, which result from relatively slow electric currents that can be measured with sufficient resolution (Fabiani et al., 2007). In fact, as action potentials consist of exceptionally rapid current flows resulting from cell depolarization, they only partially contribute to the EEG signal by influencing the local field potentials (LFP) collected by the EEG (Biasucci et al., 2019; Müller-Putz, 2020). Furthermore, it is important to consider that the degree to which EEG potentials are measurable depends on factors such as signal amplitude, the size of the synchronized region, the proportion of synchronously active cells, the amount of noise caused by the interfering of tissue layers, and location and orientation of the activated cortical region (Gevins & Smith, 2006). In regard to the last criterion, it is worth noting that, because of the very structure of the brain, EEG does not allow the measurement of deep neural structure's oscillations, where neuronal electric fields are necessarily oriented in

different directions and generally do not entail large synchronous activity, making the summation of potentials impracticable (Harmon-Jones & Beer, 2009; Lorente De Nó, 1947).

A widely practiced approach to the EEG signal implies the measurement of spontaneous EEG activity, consisting of observing the peak-to-peak amplitude of the signal generated by mental tasks. EEG signal power results from rhythmic oscillations in a frequency bandwidth ranging from below 1Hz to nearly 40Hz, but also higher frequency components have been individuated in recent years (Müller-Putz, 2020). Scientific consensus has now come to subdivide the power spectrum into five frequency bands, in virtue of their differential association with psycho-physiological processes (Schomer & Da Silva, 2012): delta (1-4Hz), theta (4-8Hz), alpha (8-13Hz), beta (13-30 Hz), and gamma (30-200Hz). In the second study of this research, we will further discuss how the identified frequency bands are linked to mental processes. Despite limited spatial resolution, EEG frequency-domain analysis allows for the study of neural oscillations with an excellent time resolution, and has brought unique contribution to the understanding of cooperative behavior during social decision-making (Moore et al., 2021), emotions' interplay with cognition (Gable et al., 2021), and complex decision-making in laboratory (Davis et al., 2011) and applied contexts, such as purchasing context (Golnar-Nik et al., 2019).

1.5.2 Electrophysiological measures for the peripheral nervous system

Skin Conductance Response (SCR)

Skin Conductance Response belongs to the heterogeneous class of psychophysiological methods that aims at measuring activity from the peripheral nervous system (PNS). By permitting communication between the brain and the periphery of our body, the PNS is in essence the vessel that mediates our interaction with the environment and makes our nervous system context-sensitive (Pessoa, 2023). Like the majority of psychophysiological techniques, SCR targets the autonomous component of the PNS (the autonomous nervous system, ANS) in light of the consolidated evidence that autonomic processes represent meaningful indirect measures of mental processes (Lin & Li,

2023). In fact, more than merely epiphenomenal, autonomic correlates are now considered to be integral to cognition, emotion, and social behavior (Critchley, 2005). Under this rationale, psychophysiological measures have been widely applied to study a range of psychological functions, including decision-making (Naqvi & Bechara, 2010), affect (Kreibig, 2010), social behavior (Schmitz et al., 2013), and their interaction (Critchley et al., 2013).

SCR specifically reflects activity from the sympathetic branch of the ANS. Mediated by acetylcholine and adrenaline, the sympathetic response determines an increase of the arousal response across the body, which involves the increase of sweat secretion by the eccrine glands. Unlike sweat glands on the rest of the body, where sweat secretion has a primarily thermoregulatory function, sweat glands on so-called “volar” surfaces (i.e., hand palms and feet) hold a unique relationship with cognitive and emotional processes that has likely evolved to favour adaptive response in the face of salient situations, such as threatening stimuli. To measure this response, SCR usually involves the application of a low voltage electric current passing between two electrodes positioned on the hand palm or fingers. As increased eccrine secretion increments the amplitude of the current, higher skin conductance is observed. As a result, an increase of arousal can be inferred (Xia et al., 2017).

Across a variety of contexts, SCR has demonstrated to be an cost-effective and solid measure bringing renewed valuable contributions to the study of decision-making (Crone et al., 2004), emotional response within social contexts (Vrana & Gross, 2004), social stress (Eisenbarth et al., 2016), and have been effectively implied in social interaction within naturalistic contexts (Hoozeboom et al., 2021)

Cardiovascular measures

Cardiovascular activity results from the complex interaction of multiple physiological systems (Pham et al., 2021). The cardiac rhythm is in fact controlled by the activity of the sinoatrial node in the first place, which is in turn regulated by a multiplicity of interacting regulatory systems and

mechanical phenomena (e.g., breathing). To a significant extent, cardiac activity is influenced by the ANS activity. Specifically, the sympathetic branch, involved in arousal and stress response (the *fight or flight* response), innervates the heart with excitatory connections and is predominantly associated to an increase of heart rate (HR). The parasympathetic branch of ANS, on the other hand, is primarily engaged during relaxed states and is associated with a decrease of HR in virtue of its inhibitory afferences. However dually innervated, the heart activity does not simply range along a sympathetic-to-parasympathetic autonomic control continuum (Berntson et al., 1993). Being influenced by several regulatory systems working on different time scales, HR shows complex patterns of variability across frequency bands, that were shown to be associated to different psychophysiological mechanisms (Pham et al., 2021). Heart rate variability (HRV), defined as the time interval between consecutive heartbeats, stands as a predominant measure of cardiac activity, which has been extensively studied due to its association with parasympathetic control (Chapleau & Sabharwal, 2011). The parasympathetic system was indeed shown to be implicated in a host of psychophysiological processes (Porges, 2007). Hence, HRV have been extensively studied as a proxy signal of emotion regulation (Chambers & Allen, 2007; Mather & Thayer, 2018), social interaction (Shahrestani et al., 2015), and decision-making (Forte et al., 2021), suggesting that inflexible patterns of HRV are reflective of hindered regulatory function of the psychopsiological systems, while higher variability reflect healthy functionality of the regulation systems, associated with a higher capacity to cope with stressors in the environment (Fabes & Eisenberg, 1997). Parallel to HRV, over several years of research, various components of cardiovascular activity have been explored in light of their connection with different psychophysiological processes, leading to the development of numerous methods for their investigation (for a complete review of these methods, we refer the reader to Berntson et al., 2007).

1.5.3 An integrated approach for complex environments

As already emerged in this introduction, cognitive neuroscience's approach is deeply rooted in a multilevel perspective (Ochsner & Kosslyn, 2013). Each level of analysis then requires its own

method. The history of cognitive neuroscience has shown, indeed, that the integration and convergence of behavioral, psychometric, and neurophysiological data is a fundamental requirement for developing accurate models of human cognitive and emotional functioning (Poldrack, 2006). By intersecting methodologies that mutually complement their respective shortcomings, each typology of data can intervene in delineating a different portion of the same picture (Ochsner & Kosslyn, 2013).

When it comes to complex environments, we contend it is of extreme importance taking into account multiple levels of analysis. As we sought to highlight across this introduction, complexity in real-world environments arises particularly in relation to emotional and social facets that are intrinsically embedded into human experience. In light of the presented weaknesses of psychometric methods in this regard, one first necessary step towards building more realistic theories of decision-making should then involve complementing the study of socio-affective processes with neurophysiological measures, in addition to the use of psychometric and behavioral data. We believe this integrated methodological approach will better help uncover the unconscious counterpart of decisional processes through the link with the underlying neurobiological mechanisms.

On the other hand, among the more recent approaches to decision-making, a less conventional sub-discipline has emerged under the name of *naturalistic decision-making* (NDM), which is concerned with investigating how decisional processes unfold in the real world, refuting artificially constrained experimental settings (Lipshitz et al., 2001). This approach places particular emphasis on how expert decision-makers make use of experience and contextual factors - such as other social agents or emotions (Mosier & Fischer, 2010) - to handle decisions (but importantly, also options generation) in difficult field settings. Although authors have contested the value of this discipline and argued that generalization of the results into a model would be unattainable as the approach is mainly aimed at providing an accurate qualitative description of the observed unique decisional processes, NDM can nonetheless come to the aid of standard decision-making theories by contributing to the building of an integrated approach (Cooksey, 2001). By supporting methodological diversity, valuing the role of the context in which decisions are embedded, embracing

complexities inherent in human behavior, and avoiding “*premature closure in our understanding engendered by the reification of the principle of parsimony and simplistic 'beauty' of linear models*” (Cooksey, 2001), decision-making theory can head towards a unified science of decision rooted on the integration of naturalistic and standard models.

In the present research, we have tried to make some of these principles ours, in an attempt to contribute to this new multidisciplinary integrated approach to decision-making.

1.6 General aims of the research

Across the introduction, we have delineated how decision-making theories have evolved in recent years, up to the latest endeavors to take advantage of the study of the neurophysiological underpinnings to uncover the mechanisms of decision-making. It has emerged from different disciplines that research in decision-making is affected by a problematic trait. In fact, the use of simplified experimental environments and streamlined theoretical models scarcely grounded on the reality of the decision-maker, as inherited by neoclassical models of decision-making, is raising criticism among various disciplines in the macro-area of decision-making research, including cognitive neuroscience (Schonberg et al., 2011), decision neuroscience (Mobbs et al., 2018), ethology (Fawcett et al., 2014), and psychology (Kingstone, 2008; Lipshitz et al., 2001). As decision rules have evolved to be adaptive in the environment (Gigerenzer, 2000; Koechlin, 2014, 2016; McNamara & Houston, 2009), studying decision-making within artificial settings has excluded from the investigation some of the core elements that are intrinsically embedded in the environment and that significantly affect human decision-making, such as emotional and social phenomena. Hence, the present research aims to contribute to the presented debate by pursuing two general objectives. First, we aim to investigate the role of emotions and social interaction in decision-making, with a view to garnering insights into their synergistic interplay with more controlled and cognitive processes. In fact, although research on the role of socio-affective components in decision processes significantly increased in recent years, the study of the neural underpinnings responsible for the interaction between decision-making, emotion processing, and social interchange is still in its infancy

(Phelps et al., 2014; Rilling & Sanfey, 2011). Furthermore, a second objective consists of exploring another pathway to understand how decisions unfold within the complexity of real environments by creating more ecologically valid experimental settings within applied fields. The effort is directed at finding a fair trade-off between external and internal validity. A twofold path is traced then. On the one hand, we aim to bring the environment into the model, by reintroducing into the equation of decision-making models two often underinvestigated components that belong to our everyday-life environments; on the other hand, we aim to bring our investigation progressively into the environment, outside of the laboratory as much as we can, by observing how decision-making unfolds into more naturalistic contexts. The hope is that this twofold endeavor can bring us one step closer to devising more realistic models of decision-making that take into account the “integrated rationality” of the decision-maker.

The present research is articulated in three studies, that progressively loosen the constraints of the laboratory settings.

More specifically, the first study is aimed at investigating the effect of emotional advertising messages on purchase decisions, to understand whether highly emotional communication relating to a critical universally shared experience - namely, the COVID-19 pandemic - may affect decision-making. Hemodynamic neural responses from the prefrontal cortex were considered, together with behavioral responses to an Implicit Association Test (IAT) and psychometric measures on perceived emotion and purchase decision.

The second study explores creative decisions within organizational environments, aiming at understanding how creative decisions are made as a result of an individual compared to an interpersonal reasoning process during a decision negotiation task. Electroencephalography (EEG) was combined with cardiovascular measures, skin conductance response, and psychometric indices of creativity to gain insights into social creative decisions.

Finally, the third study is an exploratory attempt to test the applicability of a newly developed digitalized tool for the assessment of decision-making multifacet skills within organizational settings. The study deals specifically with the tool module dedicated to decisional efficacy and builds on a

neuroscientific-based approach that leaves room for future application of neurophysiological measures.

1.7 References

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