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Review

Integrating Emotion-Specific Factors into the Dynamics of Biosocial and Ecological Systems: Mathematical Modeling Approaches Accounting for Psychological Effects

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Abstract

Understanding how emotions and psychological states influence both individual and collective actions is critical for expressing the real complexity of biosocial and ecological systems. Recent breakthroughs in mathematical modeling have created new opportunities for systematically integrating these emotion-specific elements into dynamic frameworks ranging from human health to animal ecology and socio-technical systems. This review builds on mathematical modeling approaches by bringing together insights from neuroscience, psychology, epidemiology, ecology, and artificial intelligence to investigate how psychological effects such as fear, stress, and perception, as well as memory, motivation, and adaptation, can be integrated into modeling efforts. This article begins by examining the influence of psychological factors on brain networks, mental illness, and chronic physical diseases (CPDs), followed by a comparative discussion of model structures in human and animal psychology. It then turns to ecological systems, focusing on predator–prey interactions, and investigates how behavioral responses such as prey refuge, inducible defense, cooperative hunting, group behavior, etc., modulate population dynamics. Further sections investigate psychological impacts in epidemiological models, in which risk perception and fear-driven behavior greatly affect disease spread. This review article also covers newly developing uses in artificial intelligence, economics, and decision-making, where psychological realism improves model accuracy. Through combining these several strands, this paper argues for a more subtle, emotionally conscious way to replicate intricate adaptive systems. In fact, this study emphasizes the need to include emotion and cognition in quantitative models to improve their descriptive and predictive ability in many biosocial and environmental contexts.

Keywords: biosocial dynamics; complex psychological factors; mathematical models; human psychology; animal kingdom; nonequilibrium phenomena; decision-making; brain networks; data-driven models; AI systems

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1. Introduction

Emotions are basic human experiences; they are complex mental states that include subjective sensations, physiological stimulation, and behavioral manifestations. Intriguingly, these emotional reactions can be set off by various triggers, and the same feeling can surface in different contexts. Feelings may range from beneficial states (like curiosity and delight) to detrimental ones (like wrath and fear) and elicit extensive changes in one's

behavior, as well as in one's physical, psychological, and physiological health. Emotions, with all their complexities, have a profound impact on how a person acts, interacts with others, and grows as an individual.

According to Bronfenbrenner's bio-ecological systems theory, which views development as an ongoing process involving interactions between people and their complex settings, the most effective way to understand the connection between emotional processes and human growth is to adopt this view. El et al. emphasized that biological, psychological, social, and ecological elements impact developmental outcomes across time in their model, which is based on the PPCT framework (process, person, context, and time) [1]. According to this theory, emotions are not just subjective experiences but rather interact with and shape external factors, including economic status, cultural norms, and environmental hazards.

Several ideas have been proposed over time to explain the mechanisms that underpin emotional experiences. The James–Lange hypothesis was among the first to claim that emotions are caused by interpretations of physiological changes in response to stimuli. In contrast, Cannon and Bard hypothesized that physiological and emotional reactions occur concurrently and independently, emerging from the same input [2]. Schachter and Singer's two-factor theory added a cognitive dimension, implying that emotional experiences stem from the interpretation of physiological arousal in relation to contextual signals [3]. These theoretical views emphasize the multifaceted nature of emotional processing and its integration into human behavior.

Emotions impact not just individual cognition and interpersonal dynamics, but also behavioral inclinations throughout the developmental cycle. At the macrosystem level, cultural norms and social attitudes toward emotional expressiveness influence how emotions are perceived, expressed, and regulated. Fear, rage, empathy, and excitement are examples of emotions that may drive or inhibit cooperative actions, influence decisions, and have an impact on ecological and social systems. For example, fear may increase risk aversion and drive resource hoarding or migration; empathy may improve collaboration and promote sustainability; anger or rage may cause conflict and break community cohesiveness; and excitement may stimulate collective pro-social acts. Early studies in emotion research frequently focused on defining specific emotional states and their results. Recent work by Scherer and Moors emphasizes the need to conceptualize emotion as a dynamic and developing process, driven by interconnected emotional components such as appraisal, arousal, and expressive reactions [4]. Similarly, Fry et al. explored the physiological coordination of emotional responses in children, demonstrating emotion-specific patterns of autonomic activity and developmental alterations in emotional regulation [5].

Emotions have a significant impact on the dynamics of biosocial and ecological systems. These systems are made up of interconnected biological, cultural, and social aspects, with emotions functioning as crucial mediators within these networks. The bio-ecological framework is suitable for studying how emotional regulation and perception evolve over time, especially in response to different environmental and contextual variables [6]. The incorporation of emotional variables into ecosystem-level analyses indicates an increasing realization that emotional processes have an impact on not just individuals but also collective actions and social consequences. Loreau et al. established a paradigm that connects individual attributes, species interactions, and ecosystem functioning to promote cross-disciplinary integration in ecology [7].

Self-organized criticality (SOC) expands these ideas even farther into the field of complex systems. Originally created in physics, SOC has been used to characterize how social and ecological systems show emergent behaviors and crucial transitions. Recent research by Tadić and colleagues has used SOC to simulate emotion-driven communication in social networks and information dissemination, therefore exposing the interaction between biological rhythms and social complexity [8,9]. These results suggest a basic framework among ecological, social, and emotional systems.

Biomathematics provides a strong and flexible framework for expressing the complex interactions both inside and across biological, psychological, and social systems. Though the discipline's traditional connection with the 13th-century Fibonacci sequence is well recognized, its conceptual roots go considerably farther back. Early in the 20th century, biomathematics formally became a scientific field of study thanks in great part to W. M. Feldman [10]. With the innovative work of N. Rashevsky in the 1930s, who expanded mathematical modeling to both biological and psychological spheres [11,12], this development expanded on Alan Turing's groundbreaking theory of morphogenesis, in which reaction–diffusion equations were proposed to describe pattern development in living entities [13], and marked a turning point.

Biomathematics has evolved over decades into a broad subject including fractional-order systems integrating memory effects and nonlocal interactions, continuous differential equations, and discrete-time population models [14–20]. Deeper investigation of the structural and dynamic characteristics of complex biosocial networks has been made possible by the merging of computational approaches and topological data analysis in recent years, thus augmenting the modeling terrain [21,22]. Nevertheless, there remains a noticeable gap in incorporating emotion-specific factors into the dynamics of biosocial and ecological systems, as well as their associated mathematical models. The main objective of this review is to bridge this gap.

Figure 1 presents the interdisciplinary architecture of this review article. Section 2 investigates psychological effects on human systems, including brain networks, mental disorders, and chronic physical ailments. Section 3 compares how models capture psychological impacts in humans and animals. Section 4 focuses on emotion-driven behavioral responses in ecological situations, such as fear-induced refuge utilization, inducible defense systems, prey switching, and cooperative hunting. Section 5 applies this paradigm to epidemiological modeling, highlighting the impact of psychological and emotional aspects like fear-driven contact reduction and public reaction to health treatments. Section 6 explores the integration of psychological impacts in advanced technologies, artificial intelligence, and complex systems. Section 7 covers the socioeconomic sector by stressing psychological repercussions in finance, business, and economics. Section 8 collected methods of psychological influence for decision-making. Section 9 addresses nonlocality, nonequilibrium dynamics, and complex psychological behavior. Finally, Section 10 summarizes this review and identifies the challenging areas for further interdisciplinary research. This work emphasizes that appropriate modeling and improved understanding of the complex adaptive behaviors observed in biosocial and socioecological systems depend on emotion-specific psychological aspects.

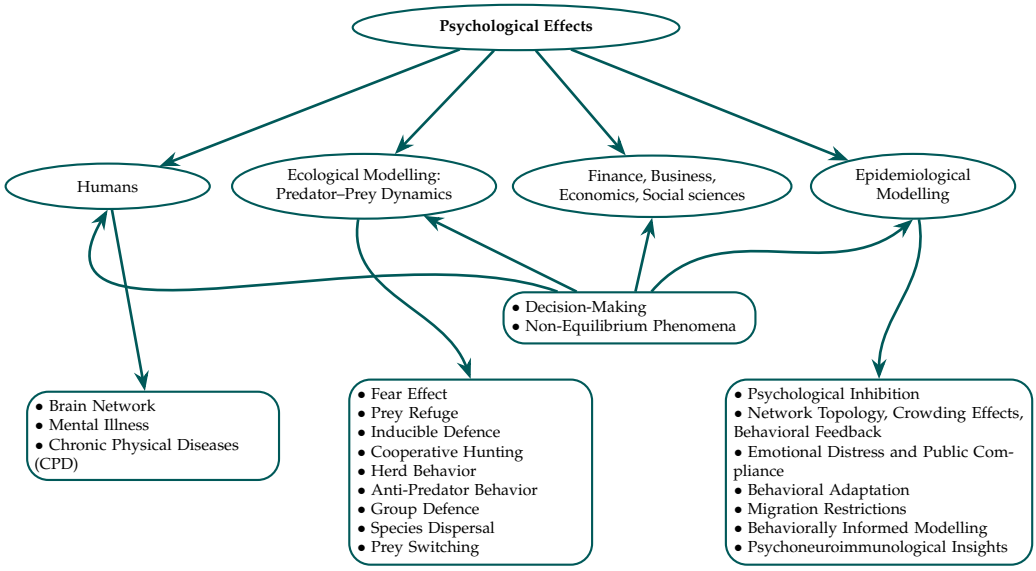


Figure 1. Schematic diagram of psychological effects and associated factors in modeling biosocial and socioecological systems.

2. Effects of Different Psychological Factors on Humans

Psychological factors significantly influence human health and well-being. Their effects influence not just mental states but also fundamental brain functions and physical health concerns across various domains. Various theoretical frameworks, including dimensional, category, and appraisal-based models, have been developed to delineate and quantify emotional processes [23]. This section provides a comprehensive overview of the interplay between the mind and body, summarizing contemporary research on the psychological effects on brain networks, the development and progression of mental disease, and the impact on chronic physical conditions.

2.1. Psychological Effects on Brain Networks

Emotional and psychological conditions significantly affect brain function across several spatial and temporal dimensions. These influences are evident in extensive network dynamics, decision-making processes, perceptual integration, and collective human behavior in high-stress situations. Psychological events emerge from nonlinear interactions among brain, cognitive, and environmental elements, prompting the development of diverse mathematical and computer models to elucidate their fundamental principles. In this part, some of the most common methods and their strengths, weaknesses, and best uses have been discussed.

2.1.1. Large-Scale Brain Networks and Emotional Modulation

The human brain functions as an interconnected, spatially organized complex network [24,25]. Large-scale resting-state networks, particularly the default mode network (DMN), encompassing areas such as the medial prefrontal cortex (MPFC), posterior cingulate cortex (PCC), precuneus, and inferior parietal cortex, exhibit significant sensitivity to emotional states. Emotion "carryover effects," wherein antecedent emotional experiences modify subsequent baseline brain states, regulate functional connections within these regions, consequently affecting cognition, attention, and behavioral inclinations. Even though it is still hard to make high-resolution cellular maps [26], mesoscopic neuroimaging always shows organizational principles including small-worldness [27], modularity [28], and fat-tailed degree distributions [29]. Muldoon et al.'s Small-World Propensity (SWP)

metric [30] enhances the quantification of small-world structure by diminishing reliance on network density, while it is still limited by imaging noise and preprocessing decisions.

2.1.2. Metabolic Constraints and Generative Modeling

The brain is confined by high energy needs [31], and its circuitry is tuned by evolution [32–35]. Shorter axonal lengths reduce metabolic costs [36–38], promoting robust short-range connections [39]. Generative models of brain networks endeavor to reconstruct such architectures by spatial embedding rules [40,41] or a combination of spatial and topological restrictions [42]. Of them, the Vértés et al. model [43] is based on physiology and finds a balance between wiring cost and topological similarity. But generative models usually make emotional and cognitive states less important by focusing on structural limitations instead of dynamic or affective modulation.

2.1.3. Emotion-Induced Collective Dynamics and Crowd Behavior

Psychological factors affect both individual neuronal function and collective human behavior. When people are under stress, such as during emergencies, their emotions, including dread and terror, affect how they move as a group. There are many other types of models that have been made to describe these kinds of group-level dynamics. Some of these are lattice-gas models [44,45], social force models (SFM) [46–54], fluid-dynamic techniques [55,56], agent-based models [57], game-theoretic models [58], cellular automata (CA) [59–67], and discrete element methods (DEMs) [68–75]. Every modeling lesson captures certain parts of how things work in the actual world [76]. SFM, for instance, combines emotional and physical forces but makes cognitive diversity and interpersonal connections easier to understand. CA models are also easy to use for computers, but they do not have adaptive intelligence or the capacity to predict what will happen. And DEM models genuinely include physical interactions, but they usually leave out memory, emotion contagion, and higher-order cognition. Consequently, although collectively informative, no singular model adequately encapsulates the multiple psychological drivers of crowd behavior. Behavioral responses induced by stress are challenging to generalize because of variability in perception, cognition, and emotional regulation.

2.1.4. Emotion and Decision-Making: Drift-Diffusion Models (DDMs)

At the individual level, psychological states strongly shape decisions. The Drift-Diffusion Model (DDM) [77–79] expresses evidence accumulation as a stochastic differential equation:

$$dx(t) = \mu dt + \sigma dW_t, \tag{1}$$

with μ representing drift (evidence strength), σ represents the noise intensity, W_t is a Wiener process, and decisions formed when $x(t)$ reaches boundaries $\pm\theta$. The DDM has been utilized to explain emotionally influenced decisions, including imitation, herding, and behaviors motivated by uncertainty [80–82], while also aligning neurobiological data with Bayesian inference concepts [83–86]. However, the DDM simplifies intricate emotional processes into a limited set of characteristics; it does not directly depict more nuanced emotional evaluations or multifaceted cognitive dynamics. Diederich and Colonius's two-stage diffusion model separates perceptual and motor stages, which makes it more granular, but it still makes affective modulation easier [87]. Affect labeling experiments show that emotions can be quickly brought down, which is in line with how the prefrontal cortex and amygdala work together [88]. However, these studies have some problems because of noise from sentiment analysis and changes in the real world. Research on multisensory integration indicates that perceptual ambiguity influences emotional state; yet, computer models are limited by their representational simplicity [89–92]. Thieu and

Melnik integrate Bayesian inference into the DDM to simulate variable emotional states in dynamic environments [93,94]. Their models enhance psychological realism but necessitate significant parameterization.

2.1.5. Advances in Psychophysics, Signal Processing, and Computational Emotion

Recent techniques like continuous psychophysics [95,96] and behavioral signal processing (BSP) [97] let us measure emotion–behavior connections in great detail. These technologies show how linguistic patterns, predictive coding signals, and oscillatory dynamics are all connected [92,98,99]. Even though they are very accurate, these frameworks usually only look at one type of modality at a time, which makes it hard for them to see the whole picture of emotional processes. Emotion modeling has benefited from Ambrosio's wave-based model [100] as well as Mattek et al.'s valence–arousal dynamics [101]:

$$\frac{d\mathbf{\Psi}}{dt} = \mathbf{F}(\mathbf{\Psi}), \tag{2}$$

where $\mathbf{\Psi}$ denotes the emotional state vector and $\mathbf{F}(\cdot)$ specifies its intrinsic dynamics.

With emotional surges represented using the following equation:

$$G(x, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{x^2}{2\sigma^2}}, \tag{3}$$

where $G(x, \sigma)$ is a Gaussian surge function, x represents deviation from baseline, and σ controls the width (intensity spread).

And emotional decay is governed by the following equation:

$$\frac{d\sigma}{dt} = -(a - \alpha(t))\sigma, \quad \alpha(t) = ct. \tag{4}$$

Here, σ is the activation spread, a is the baseline decay constant, and $\alpha(t)$ is a time-varying modulation term with rate c. These low-dimensional formulations provide interpretability but fail to properly encapsulate multidimensional affective feelings. Complementary methodologies encompass Affect Control Theory [102], EEG-based emotion recognition [103], RL-based emotional assessment [104], free-energy minimization frameworks [105,106], dual-process neural architectures [107], and CAKE networks [108]. Each one captures certain parts of how emotions are processed, but they cannot be used in other modeling contexts. Predictive coding and multimodal neuroscience research underscore the dispersed brain representations of emotion [109–113], whereas neuroeconomic studies elucidate the emotional influences on valuing systems [114]. Hierarchical brain networks demonstrate self-organized criticality (SOC) [8], potentially facilitating adaptability; nevertheless, their direct correlation with subjective emotional experience is still contested. Prediction-error signals in the insula play a role in anxiety and other illnesses [115]. Information-theoretic restrictions influence the development of adaptive brain and social systems [116–120].

2.1.6. Stochastic Modeling of Emotional Dynamics

Carbonaro and Serra [121] propose an integro-differential emotional interaction model:

$$\frac{\partial \pi_{ij}(x, t)}{\partial t} = \tau_{ij}([\pi_{hk}]), \tag{5}$$

where τ_{ij} describes how interacting emotional distributions evolve. Although conceptually powerful, empirical validation is limited due to challenges in real-time parameter estimation.

Psychological factors influence brain dynamics at various levels, ranging from neuronal circuits to collective social behavior. Stochastic differential equations, generative connectome frameworks, and crowd simulations are some of the models that try to show how complicated this is. However, each one has its own limitations, and they frequently make affect, cognition, or context easier to understand mathematically. To make sure these models are used correctly and do not go too far in their ideas, we need a clear view of them at all levels. Neurobiological network models and dynamic representations of emotion collectively illustrate the pivotal role of affect in influencing brain activity, individual behavior, and collective cognition. Subsequent research ought to pursue integrative frameworks that amalgamate neuroscience, computer modeling, and psychology theory to elucidate the dynamic influence of emotional states on cognitive and social processes.

2.2. Psychological Effects on Mental Illness

Mental disease is a complex phenomenon resulting from the interplay of neurobiological, cognitive, psychological, environmental, and societal components. Disorders like depression, anxiety, PTSD, OCD, and schizophrenia show changes in neurotransmission and brain network connections that affect cognitive control, emotion regulation, memory, and decision-making [122]. Models that incorporate psychological aspects are crucial for comprehending the onset, progression, and treatment response to mental illness, as it is influenced by the dynamic interplay between the individual and their environment.

2.2.1. Stigma, Cognitive Appraisals, and Social Context

The psychological consequences of mental disease surpass mere clinical manifestations. Stigma has a big effect on how happy people are with their lives, how they see themselves, and how quickly they recover. Anticipated rejection and discrimination exacerbate anxiety and depression [123]. Interestingly, the sort of explanatory model employed might affect stigma. For example, biological explanations can lessen blame but may make others think someone is more dangerous, while psychological explanations can lessen stigma by focusing on how to control and recover from a problem [124]. Mental illness has a big impact on family structures. Caregivers feel emotionally burdened and less healthy, especially when they are short on money [125]. Parental mental illness interrupts children's development by affecting the quality of care and the stability of their surroundings [126]. There is a link between marital status and psychological resilience [127]. Single and widowed people tend to be more distressed. The COVID-19 pandemic exacerbated symptoms in persons with pre-existing mental problems [128,129].

2.2.2. Illness Perceptions and Emotional Regulation

The Self-Regulation Model (SRM) [130] asserts that individuals' perceptions of their condition influence coping mechanisms, emotional reactions, and long-term results. Caregivers experience increased distress when disease is ascribed to moral failing or controllable behavior [131,132]. Patients who think that auditory hallucinations are evil or all-powerful are more likely to be depressed and hurt themselves [133,134]. Cognitive–behavioral therapy (CBT) changes these harmful ideas, which makes the symptoms less severe [135]. How people think about the effects of disease can indicate how much stress it will cause for both patients and their families [136]. Stigma by association causes emotional stress and even thoughts of suicide in family members [137]. Depression and retreat are associated with a perceived loss of autonomy and social devaluation [138,139]. Media portrayals reinforce negative prejudices even more [140–143]. Preventive therapies, such as cognitive-behavioral therapy (CBT), family-based therapy, and parenting programs, reliably diminish risk factors and enhance results [144–150]. These kinds of approaches show how important psychological aspects are in both starting and becoming better.

2.2.3. Physiological and Developmental Mechanisms

Recent studies emphasize significant psychophysiological factors influencing emotional dysregulation. Autonomic synchronization between sympathetic and parasympathetic systems seems to influence subsequent emotional stability. Fry et al. discovered that inadequate coordination during avoidance-related emotions (fear and sadness) forecasts subsequent instability, whereas reciprocal cooperation during approach-related emotions (happiness and rage) fosters more adaptive developmental trajectories [5]. These results underscore the significant influence of early physiological processes on susceptibility to depression, anxiety, and associated illnesses. Developmental pathways also interact with psychological issues. Negative experiences in childhood, pressures in the social and environmental spheres, and early challenges in regulating emotions collectively elevate the risk of mental health issues. These interrelated pathways underscore the necessity for modeling frameworks that incorporate psychological, developmental, and physiological aspects.

2.2.4. Mathematical and Computational Modeling of Psychopathology

Computational psychiatry is increasingly dependent on mathematical models to systematize the emotional and cognitive mechanisms that lead to mental disease [115]. These methods give us a better understanding of how things work, but they also make things too simple, so it is crucial to be clear about what they can and cannot do.

Dynamical systems models present a method for encapsulating emotional processes. Mattek et al. employ systems of differential equations to model the relationships between stress, affect, and brain circuits, including the amygdala and ventral striatum [101]. Roberts et al. create a neurocomputational architecture that separates the creation of affective states from the calculation of values [151]. This lets emotional valence change how evidence builds up over time. Even though these models help us comprehend theory better, they are still only ideas because it is hard to precisely set parameters for real-world emotional states and contextual conditions. Another significant avenue arises from the modeling of cultural heterogeneity in emotional processes. Chen et al.'s meta-analysis of data from 37 nations indicates that cognitive reappraisal is generally linked to less psychopathology, but expressive suppression yields effects that vary significantly depending on cultural norms [152]. The research additionally associates uncertainty avoidance and long-term orientation with regulatory efficacy. These findings emphasize the constraints of universal modeling assumptions and illustrate the necessity for computational frameworks that integrate cultural context.

2.2.5. Dialectical Behavior Therapy (DBT): Mathematical Representations

Linehan came up with DBT, which is a well-known treatment for borderline personality disorder, emotional dysregulation, suicidality, and impulse-control issues [153,154]. Researchers have utilized mathematical models to copy their main processes, which shows how useful they are for controlling behavior and emotions [155]. Adding positive behavior patterns and tactics for forming habits to evidence-based therapy makes them even more beneficial in the long term [156]. So, mathematical formulations serve to make DBT's mechanisms more formal and clear.

(1) Dynamical systems model: DBT intervention can be articulated as follows:

$$\frac{d\mathbf{x}(t)}{dt} = \mathbf{f}(\mathbf{x}(t), \mathbf{u}(t), \boldsymbol{\theta}), \tag{6}$$

where $\mathbf{x}(t)$ is the emotional state vector, $\mathbf{u}(t)$ is the intervention vector (like mindfulness or distress tolerance), and $\boldsymbol{\theta}$ is the set of parameters that are unique to each individual. These

models demonstrate how structured skills training influences emotional trajectories, while empirical parameterization is difficult.

(2) Reinforcement learning interpretation: DBT can be conceptualized as a reward-based learning process, exemplified by Q-learning:

$$Q(s,a) \leftarrow Q(s,a) + \alpha \left[r + \gamma \max_{a'} Q(s',a') - Q(s,a) \right], \tag{7}$$

which is backed up by studies in psychopathology [157,158]. This concept emphasizes the acquisition of adaptive skills while oversimplifying emotional complexity.

(3) Stochastic differential equations for mood volatility: Stochastic dynamics capture emotional fluctuations:

$$d\mathbf{x}(t) = -\lambda \mathbf{x}(t)dt + \sigma d\mathbf{W}_t + \mathbf{u}(t)dt, \tag{8}$$

where $\mathbf{u}(t)$ is the DBT intervention vector. λ is the natural recovery rate; $\sigma d\mathbf{W}_t$ signifies stochastic affective perturbations; $\mathbf{x}(t)$ represents emotional dysregulation. This approach tracks mood variability over time [159,160].

(4) Network modeling of psychiatric symptoms: In network analysis, symptoms are thought of as nodes and how they interact with each other as edges [161,162]. DBT diminishes maladaptive connections and fortifies adaptive patterns; nonetheless, the longitudinal stability of these networks remains challenging to validate.

Table 1 brings these mathematical representations together and shows how each framework shows how DBT affects people's minds.

Table 1. Mathematical models capturing DBT's psychological impact.

Model Type	Mathematical Tool	Equation	DBT Influence
Dynamical Systems [163,164]	Differential Equations	$\frac{dx(t)}{dt} = f(x(t), u(t), \theta)$	stabilizes emotional trajectories via control input
Reinforcement Learning [157,158]	MDP+Q-learning	$Q(s,a) \leftarrow Q(s,a) + \alpha[r + \gamma \max Q(s',a') - Q(s,a)]$	reinforces skill acquisition through adaptive decision-making
Stochastic Modeling [159,160]	Stochastic Diff. Equation	$dx(t) = -\lambda x(t)dt + \sigma dW_t + u(t)dt$	reduces mood volatility and increases emotional resilience
Network Analysis [161,162]	Graph Theory	Network structure of symptoms and skills	weakens maladaptive links, strengthens adaptive psychological nodes

2.2.6. Emerging Therapies and Neurocomputational Developments

Innovative approaches like ayahuasca-assisted therapy facilitate emotional catharsis and reflection, supported by neuroimaging studies indicating modification in the amygdala and anterior cingulate cortex [165–169]. The two-continua model of mental health makes a clear distinction between having a mental disease and having good mental health. It emphasizes that flourishing means being emotionally, psychologically, and socially healthy [170,171]. AI-driven affective computing systems enhance the identification and support of mental health disorders [172]; however, apprehensions persist around algorithmic bias, cultural dependency, and limitations in real-world implementation.

Psychological factors affecting mental disease arise from the complex interplay of emotion control, cognitive assessment, physiological reactivity, familial context, and cultural standards. Mathematical and computer models provide significant mechanistic insights into these processes; yet, they are simplifications limited by parameter uncertainty, cultural diversity, and real-world complexity.

In broad strokes, mental illness has effects on a person's mind, body, family, and social life. For long-lasting healing and emotional strength, treatments that combine these areas and are based on data and experience are needed.

2.3. Psychological Factors in Chronic Physical Diseases (CPDs)

Chronic physical diseases (CPDs), such as cardiovascular illnesses, diabetes mellitus, neoplastic problems, chronic respiratory diseases, arthritis, and osteoporosis, represent a significant global health burden, severely diminishing quality of life (QoL) and subjective well-being [173]. With diverse etiologies and illness trajectories [174], chronic physical disorders (CPDs) not only advance physically but are also profoundly connected to psychological, emotional, and cognitive components. Mental comorbidities increasingly affect the onset, progression, and management of chronic pain disorders (CPDs) [175], rendering psychological factors fundamental rather than ancillary to the comprehension of illness outcomes. This part synthesizes empirical, theoretical, and computational discoveries that link psychological processes to the course of chronic pain disorders (CPDs).

2.3.1. Bidirectional Links Between CPDs and Psychological Distress

A substantial amount of research demonstrates a significant bidirectional relationship between chronic pain disorders (CPDs) and psychological conditions, including anxiety, depression, emotional dysregulation, and sleep difficulties [176–179]. These interactions are not solely correlational; mental distress frequently exacerbates physical problems and vice versa. Research on fibromyalgia, diabetes, psoriasis, and osteoporosis shows that sensations of depression and anxiety are closely linked to how bad the disease is, how much inflammation is going on, and how bad the pain is [176,180–186]. Cross-sectional and longitudinal studies validate that chronic pain disorders (CPDs) can impair cognitive performance, emotional regulation, and stress reactivity [187–189]. Simultaneously, psychological disorders can aggravate illness progression, obstruct adherence to medical directives, and impede healing, demonstrating the reciprocal relationship between mental and physical domains.

2.3.2. Mathematical and Computational Perspectives on Emotional Regulation in CPDs

Carrero et al. [190] provide a nonlinear dynamical system that illustrates happiness via both hedonic and eudaimonic dimensions. Their paradigm connects emotional modulation to physiological stress responses, creating a conceptual link to psychosomatic mechanisms in chronic pain disorders (CPDs). The model, though abstract, illustrates how prolonged emotional dysregulation might exacerbate chronic illness outcomes via the activation of stress pathways. Complementary empirical findings by Fan et al. [88] and Chen et al. [152] demonstrate that affect naming and cognitive reappraisal swiftly diminish emotional intensity. These top-down regulatory techniques may mitigate stress-induced physiological cascades, potentially reducing systemic inflammation and cardiovascular risk. Their research indicates psychosomatic advantages in various cultural contexts; however, generalizability is constrained by variations in cultural norms and emotional expression. These studies collectively endorse the concept that emotional processing constitutes an active physiological mechanism, rather than solely an epiphenomenon, influencing disease regulation.

2.3.3. Cognitive Deficits and Pain Amplification Mechanisms

Cognitive deficits are common among individuals with CPD. Neuropsychological evaluations reveal that metabolic imbalance, chronic inflammation, and concomitant psychological distress cumulatively lead to impairments in attention, memory, and executive functioning [191]. Pain perception is especially susceptible to emotional instability. Catastrophizing, the cognitive propensity to exaggerate pain feelings, exacerbates pain experiences and amplifies physiological reactions. Research indicates that this effect is particularly significant in young female patients having diagnostic or invasive procedures [192,193].

These results underscore the need for psychological evaluations as essential elements of comprehensive Continuing Professional Development (CPD) management strategies.

2.3.4. Developmental, Psychosocial, and Neurobiological Contributors

Longitudinal data indicate that early-life stressors influence adult susceptibility to chronic physical disorders (CPDs). Stressful life events (SLEs) induce enduring modifications in lipid metabolism, emotional stability, and cognitive functioning [194]. Neurodevelopmental disorders like ADHD also make people more likely to have long-term emotional and cognitive problems, and they often make them worse when they have other conditions like PTSD or persistent emotion suppression [195–198]. These results underscore that CPD consequences cannot be comprehensively elucidated without accounting for developmental histories, psychosocial circumstances, and enduring regulatory trends.

2.3.5. Role of AI and Emotional Computing in CPD Management

Emotional computing has started to help with integrated care, even though it has not been talked about as much in traditional CPD literature. For example, AI tools that use music can change emotional states and lower stress levels [172]. These approaches show early promise for enhancing affective stability in CPD patients but require extensive clinical validation and long-term outcome assessments.

2.3.6. Psychological Interventions and Interdisciplinary Care

Effective CPD management increasingly necessitates interventions that address psychological processes along with physical symptoms. Programs that include psychoeducation, mindfulness-based cognitive therapy, non-invasive brain stimulation, and peer support have a lot of positive effects on both mental and physical health [199–203]. These treatments assist patients in managing their stress, staying emotionally stable, and sticking to their medical treatments.

The relationship between psychological factors and CPDs is bidirectional, dynamic, and complex. Psychological stress, emotional dysregulation, and cognitive deficiencies are not merely outcomes of chronic disease; they actively facilitate its advancement. Mathematical models offer conceptual clarity, empirical research validates physiological systems, and AI-driven technologies propose future trajectories for integrative therapy.

Reiterating the intricacy and interrelation of these effects, the consideration of several psychological elements in this part clarifies their great influence on human cognition, emotion, and behavior. These results highlight the need for complex models able to authentically depict human psychological processes. We will now advance to assess the generalizability of psychological models and investigate whether knowledge gained from human studies can sufficiently guide animal behavior research. Aiming to find both convergent trends and important differences, Section 3 transforms into a comparative investigation of model formulations in human and animal psychology in view of this. This analogy helps one to grasp the degree of common psychological systems between animals and their differences.

3. Similarities and Differences in Model Formulation: Human and Animal Psychology

Although human and animal psychology have fundamental cognitive and behavioral ideas, variations in cognitive complexity, emotional control, and sociocultural factors cause significant mathematical modeling variance between them. Although they use dynamic systems, stochastic processes, game theory, and control frameworks, both fields have quite different presumptions, variables, and modeling scope. To explain adaptive behavior, both

fields apply dynamic systems theory, stochastic processes, game theory, and optimal control frameworks; nonetheless, the presumptions, variables, and scope vary significantly.

3.1. Shared Mathematical Foundations

Behavioral modeling is fundamentally based on the application of differential equations to characterize changes between psychological or behavioral states throughout time. One may represent a broad dynamical system relevant in both human and animal environments as follows:

$$\frac{d\mathbf{x}(t)}{dt} = f(\mathbf{x}(t), \mathbf{u}(t), \boldsymbol{\theta}), \tag{9}$$

where $\mathbf{x}(t)$ marks the internal behavioral or psychological state vector, $\mathbf{u}(t)$ shows the external stimuli or environmental input vector, and $\boldsymbol{\theta}$ is a parameter vector encoding individual attributes (e.g., risk aversion; memory span). Based on these inputs and settings, the function f controls the evolution of the system.

3.2. Animal Psychology Modeling

Evolutionary forces have developed animal cognition to be essentially focused on immediate survival and reproduction. Behavioral ecology models center on basic, survival-oriented tactics like risk avoidance, optimum foraging, and predator–prey interactions. Usually founded in biological realism, these actions are portrayed either deterministically or stochastically.

Population dynamics is extensively represented via classical models such as the Lotka–Volterra predator–prey equations [204,205]. Extensions of these models include behavioral feedback derived from optimum foraging theory, ideal free distribution [206], and eco-epidemiological links between behavior and disease transmission [207,208]. Usually reinforced with fear-induced dynamics or energetic trade-offs [209,210], these are described using extensions of classical models such as the Lotka–Volterra equations. Usually motivated by biological needs like survival and reproduction, these imply consistent actions [211].

In animal models, psychological impacts are usually limited to evolutionarily conserved features. Through tractable mathematical approaches, Lima and Dill [212] and Sih et al. [213] included anti-predator behaviors, such as alertness and habitat avoidance, into ecological frameworks. For optimal foraging theory (OFT), for instance, an animal is supposed to maximize net energy gain:

$$U = \int_0^T (R(t) - C(t))dt, \tag{10}$$

where $R(t)$ is the resource intake rate, $C(t)$ signifies the energetic cost of foraging, and T denotes the total foraging time [210,214,215].

Fear-induced behavioral alterations are a psychological extension of these theories. For example, predator-induced prey growth under fear might be defined as follows:

$$\begin{cases} \dfrac{dN}{dt} = rN - aNP, \\ \dfrac{dP}{dt} = baNP - dP, \end{cases} \tag{11}$$

where $N(t)$ and $P(t)$ denote prey and predator populations, r is the prey growth rate, a is the predator's attack rate, b is the conversion rate, and d is the predator death rate.

Behavioral extensions include psychological factors such as fear. For instance, predator-induced prey growth can be modeled as follows:

$$\frac{dN}{dt} = [r_0 f(k,P)](k,P)N - dN - aN^2, \tag{12}$$

where $f(k,P) = 1/(1+kP)$ is a function that accounts for the cost of anti-predator defense due to fear [209]. Other models include anti-predator behaviors, including habitat shifting and awareness [212,213].

3.3. Human Psychology Modeling

In contrast, human psychology includes higher-order cognition, metacognition, emotional variety, and cultural embedding. Modeling frameworks must account for abstract thinking, social impact, and dynamic emotional states [216–220]. Human emotional reactions go beyond survival and encompass complex emotions like guilt, shame, pride, or existential worry [221–223].

Human decision-making models frequently rely on reinforcement learning (RL), in which adaptive methods emerge via trial and feedback:

$$Q(s,a) \leftarrow Q(s,a) + \alpha \left[r + \gamma \max_{a'} Q(s',a') - Q(s,a) \right], \tag{13}$$

where $Q(s,a)$ is the value of action a in state s, α is the learning rate, γ is the discount factor, and r is the reward.

Prospect Theory incorporates distortions in value and probability evaluations to account for cognitive biases and perceived risk:

$$U = \sum_i w(p_i), v(x_i), \tag{14}$$

in which the subjective value function is $v(x_i)$, and the probability weighting function is $w(p_i)$ [224,225].

Delay differential equations (DDEs) sometimes help to represent cognitive memory and emotional inertia:

$$\frac{d\mathbf{x}(t)}{dt} = -\lambda \mathbf{x}(t) + \beta \mathbf{x}(t-\tau), \tag{15}$$

where τ is a memory lag; $\mathbf{x}(t)$ is a vector-valued function characterizing the state of a cognitive or emotional system at time t. β catches feedback intensity. Rumination, expectation, and delay emotional inertia in cognition are explained using these equations.

To grasp collective actions and internal-emotional states, human psychology also mostly depends on agent-based modeling, social norm learning, and neural networks [226–229].

Furthermore, sociocultural models have their own importance. Schelling's segregation model shows how straightforward choices may produce intricate social structures [230]. While some animals exhibit basic culture, i.e., tool usage in chimpanzees or birdsong transmission [231,232], they lack the symbolic, cumulative richness of human society, which significantly influences cognition, emotion, and decision-making [233]. Human self-awareness brings existential questions and moral reasoning. Although some animals show self-awareness [234–237], psychological dynamics are much influenced by the introspection complexity of humans. Even though behavioral complexity, including fear and learning, is becoming more acknowledged in animal models, they remain simpler and more predictable. Behavioral patterns are typically motivated by physiologically ingrained needs, even in highly evolved species [238]. Human behavior, on the other hand, requires dynamic, probabilistic models reflecting cognitive, emotional, and cultural variety. Table 2 lists the

main aspects along which mathematical models of human and animal psychology differ and converge.

Table 2. Key distinctions in psychological modeling frameworks for animals and humans.

Modeling Dimension	Animal Psychology	Human Psychology
Focus of primary modeling	Adaptive behavior for survival and energy efficiency	Emotional regulation, cognitive processing, social conformity
Representative modeling approaches	Optimal foraging theory, predator–prey dynamics, signal detection models	Reinforcement learning, prospect theory, agent-based models, delay differential equations
Learning and adaptation mechanisms	Classical and operant conditioning, basic reinforcement learning	Meta-learning, Bayesian belief updating, affect-biased decision-making
Nature of feedback	immediate, environmentally contingent	Delayed, emotionally charged, and socially contextualized
Neural and cognitive representations	Implicit or species-constrained neural substrates	Explicit neural correlates (e.g., prefrontal cortex, limbic system, DMN)
Cognitive and systemic complexity	Low to moderate, domain-specific	High-level integration across cognitive, emotional, and sociocultural domains

3.4. Neurophysiological Integration

Human psychological models increasingly combine neurophysiological elements. For instance, dynamic models of the default mode network (DMN) integrate emotional control by means of linked neuronal activity:

$$\frac{d\mathbf{x}}{dt} = -\mathbf{A}\mathbf{x} + \mathbf{I}(t), \tag{16}$$

where $\mathbf{x} = (x_1, x_2, \ldots, x_n)^T$ is a vector of neural activities across brain regions. Also, $\mathbf{A} = [A_{ij}]$ denotes the connectivity matrix encoding interaction strengths between regions i and j, and $\mathbf{I}(t) = [I_j(t)]$ represents a vector of time-varying external or emotional inputs [24,239].

Animal models frequently give evolutionary stability and ecological simplicity paramount importance, even if they progressively include behavioral complexity like learning, emotion, and fear reactions. Human models, on the other hand, demand flexible, probabilistic, multi-scale methods that fully reflect cognitive and social variation.

This comparative framework shows common mathematical underpinnings together with species-specific behavioral adaptations in emotional control and decision-making. Knowing these parallels and contrasts helps one to design species-specific methods or to generalize psychological modeling ideas across animals. Bridging this understanding is particularly crucial in ecological modeling, where animal behavior—especially fear, learning, and risk perception—directly shapes population dynamics and ecosystem resilience. Emphasizing predator–prey interactions, the following section looks at these psychological impacts on ecological systems.

4. Psychological Effects in Ecological Modeling: From the Perspective of Predator–Prey Interactions

An ecosystem is a sophisticated, biodiverse system whereby dynamic interactions between living entities interact with their nonliving surroundings. Particularly in connection with sustainability and species coexistence, ecological study depends on an awareness of these relationships. Among the fundamental subjects in ecological modeling, the dynamics of predator–prey interactions have long been a theoretical and mathematical pillar. Malthus initially proposed the idea, then Verhulst improved it; finally, Lotka [240] and Volterra [241] formalized it into deterministic models. These models have changed dramatically over time to incorporate biological realism and behavioral complexity, like fear effects [242–244], cooperation [245–248], etc. Actually, it was discovered that the predator interference equally participates in the hunting strategy, even though these interactions were originally studied

on the presumption that only the density of a prey species could define the consumption strategy of the predator [249–251].

In a wider context, direct psychological impacts are behavioral modifications in species resulting from cognitive reactions and observation instead of physical interactions. One of the most explored is the fear effect, wherein prey change their foraging, mobility, or reproductive tactics in response to feared predation, thereby often lowering activity even in the absence of predators. Prey refuge is the closely related idea wherein stress and anxiety force animals into spatial separation from predators or hiding. Another important mechanism is inducible defense, in which prey create behavioral adaptations like increased alertness or evasive movement depending on past predator experiences or environmental signals. These consequences fundamentally change prey dynamics and, thus, the predator–prey interaction itself.

Apart from these direct impacts, indirect psychological elements also significantly shape predator–prey systems. To increase efficiency in coordinated hunting, predators rely on learned coordination, memory, and intra-group trust. On the other hand, prey species show group defense mechanisms shaped by social learning and warning signals, therefore promoting coordinated responses even in the absence of direct threats. Usually motivated by social contagion and anxiety, herd behavior results in group movement patterns and panic reactions. In a similar vein, species movement or dispersal can be driven by perceived danger or psychological stress related to predation or competition, and prey switching reflects predator decision-making informed by memory and past success rates. These indirect systems show how profoundly psychological elements like learning, social influence, and perception are embedded within ecological interactions.

More specifically, whereas ecological and evolutionary elements mostly drive these predator–prey behaviors, their psychological elements originate from observation, learning, decision-making, and social influence. Predator–prey relationships are greatly shaped by the way different creatures understand dangers, organize activities, and react to previous events.

4.1. Fear Effect on Prey

Predators directly and indirectly influence the growth of their prey. While direct impacts include the immediate eating of prey, indirect or non-consumptive effects, especially fear, can greatly influence prey behavior, physiology, and existence [212,252]. Many times, fear of predation sets off persistent psychological stress that results in changed locomotion, less foraging, and less successful reproduction. Sometimes these consequences brought on by fear exceed those of actual predation. Pangle et al., for example, showed that in Lakes Erie and Michigan, the presence of spiny water fleas (Bythotrephes longimanus) virtually diminished the growth rate of zooplankton prey sevenfold by fear alone, compared to direct ingestion [253].

Behavioral alterations motivated by fear have been extensively recorded. Prey usually choose environments with less predation risk that still provide access to enough food [254,255]. Young backswimmers, for instance, avoid adult cannibalistic conspecifics by feeding in safer but maybe less productive habitats [256]. By altering prey vigilance and spatial utilization, apex predators like sharks and wolves can cause trophic cascades through non-consumptive impacts, therefore indirectly altering the structure and function of an ecosystem [257,258]. Fear influences the most important activities, including hunting and reproduction [259,260].

Understanding the fear impact and quantifying it have been greatly aided by mathematical modeling. Among the first to replicate predator–prey interactions with lower prey

reproduction resulting from fear was Wang et al. [209,261]. Since then, several functional forms have been suggested to mathematically capture the dread impact:

$$f(\alpha, P) = \frac{1}{1+\alpha P}, \frac{1}{1+\alpha_1 P+\alpha_2 P^2}, \frac{e^{-\alpha P}}{1+\omega \sin \alpha P} \ (0<\omega<1) \tag{17}$$

where α represents the fear level, and P represents the predator biomass. These functions are designed to satisfy key properties such as decreasing with both α and P, and tending toward 1 in the absence of fear or predators. Building on this foundation, Sarkar et al. [262] introduced the concept of a minimum fear cost. This led to a modified saturated fear function proposed by Dong et al. [263]:

$$f(\alpha, \eta, P) = \eta + \frac{1-\eta}{1+\alpha P}, \ \eta \in (0,1), \tag{18}$$

where η captures the baseline reproductive potential under extreme fear, and P is the predator biomass.

Quite a bit of research has expanded these models by including fear effects into deterministic, stochastic, fractional, and time-delayed models. These comprise studies of Hopf bifurcations [209,264–268], memory effect [269–271], tri-trophic food chains [242,272], stochastic impacts [273–276], and delay-induced behavioral switches [274,277–284]. Furthermore, the terror impact of adult predators has been investigated in a stage-structured model [285]. Published studies particularly suggest that fear might even stabilize systems displaying chaotic dynamics [286,287].

The spatial and temporal effects of fear have recently come into focus. Pattern development in models with self- and cross-diffusion have been studied [283,288–296]. Incorporating nonlocal fear effects to represent predator influences that reach across space is another step forward [297–300].

These studies taken together emphasize the important and sometimes underestimated part fear plays in predator–prey interactions. Including fear into ecological models improves not just our theoretical knowledge but also provides useful information on how to manage ecosystems where behavioral reactions are as powerful as physical interactions.

4.2. Prey Refuge

The idea of prey refuge has been thoroughly investigated in mathematical and ecological domains due to its importance in predator–prey interactions. Prey species are able to maintain stable populations in biological systems thanks in part to refuges, which are places or circumstances where they may escape predators [301,302]. By offering partial shelter for prey, these refuges lessen the danger of extinction caused by predators. Prey refuge frequently stabilizes the dynamics of predator–prey models, as shown by early experimental data by Gause and later theoretical advances [303]. In particular, Ruxton demonstrated that stabilizing effects are manifest in the system when the rate of prey entering the refuge is directly proportional to predator density [304]. To ensure that refuge-based models are stable, Du and Shi [305] and Huang et al. [301] presented analytical requirements. Using diffusive models with Michaelis–Menten response, Wang & Wang [306] and Lv et al. [307] both found similar results in two-patch ecosystems. Two common types of prey refuges are those with a set maximum capacity and those where the number of refuges scales with the size of the prey population [265,272,276,281,298,308–314].

Multiple refuge forms have been mathematically modeled, with N representing prey biomass and P representing predator biomass:

(i) Refuge proportional to the prey population:

$$\frac{dN}{dt} = f_1(N,P) - q(1-m)NP, \quad \frac{dP}{dt} = q(1-m)NP - f_2(N,P). \tag{19}$$

(ii) Constant refuge population:

$$\frac{dN}{dt} = f_1(N,P) - q(N-m)NP, \quad \frac{dP}{dt} = p(N-m)NP - f_2(N,P). \tag{20}$$

(iii) Refuge proportional to the predator population:

$$\frac{dN}{dt} = f_1(N,P) - q(1-mP)NP, \quad \frac{dP}{dt} = p(1-mP)NP - f_2(N,P). \tag{21}$$

(iv) Refuge proportional to both prey and predator population:

$$\frac{dN}{dt} = f_1(N,P) - q(N-mP)NP, \quad \frac{dP}{dt} = p(N-mP)NP - f_2(N,P). \tag{22}$$

The presence of a refuge can stabilize or destabilize the system, according to theoretical research, depending on the unique model structure and parameter choices [266,268,275,315–320]. From the perspective of functional reactions and refuge mechanisms, Olivares and Jiliberto [321], as well as Ma et al. [322], noted impacts that were both stabilizing and destabilizing. Refugees are ecologically relevant, according to empirical evidence. As an example, semi-aquatic animals such as mouse-deer seek refuge in bodies of water [323], and rats conceal themselves in thick foliage [324] to ward off predators. Behavioral adaptations, like diel vertical migration in marine habitats, can further aid animals in evading visual predators by providing temporary refuges [325]. The size-based refuge is another critical component. Prey that is smaller can hide in cracks and microhabitats, whereas prey that is larger may be more easily caught because of their bigger size [326]. Both biodiversity and prey survival are improved by physical havens, such as seabird islands free of predators or marine protected areas [327,328]. More ecological mechanisms have been incorporated into refuge models in recent writings. By factoring in wind factors, Takyi et al. demonstrated that refuge led to a decrease in predator density and an increase in prey density [329]. Whereas Khan and Alsulami examined discrete models with refuge-induced complexity [330], Manaf and Mohd investigated the combined effects of herd behavior and refuge [331]. Stephano and Jung looked at how immigration and prey refuge affected populations, and they found that the two factors had a disproportionate impact [332]. In contrast, the work of Chauhan et al. examines a predator–prey model that incorporates anti-predator effects, prey refuge, and threat aversion [271]. Upon approaching prey refuge and fear level thresholds, their analysis shows that coexistence changes from stable to oscillatory. In conclusion, research in theory and practice supports the idea that predator–prey dynamics are significantly impacted by the availability of predator–prey refuge. Ecological systems benefit from refuges because they increase prey persistence, decrease predation pressure, and build stability over time.

4.3. Inducible Defense

When prey senses a predator's threat, it may show phenotypically flexible features called inducible defenses. These structural, behavioral, or functional alterations can act as adaptive mechanisms. Behavioral responses are disproportionately influenced by cognitive processes, including perception, memory, fear conditioning, and decision-making under uncertainty, when compared to well-documented anatomical and physiological barriers.

Prey respond to predator signals by changing their hunting behavior, habitat use, or time of activity, therefore avoiding direct confrontations. Should predation risk remain constant, stress-induced adaptations can also influence overall well-being, reproduction, and growth. Social interactions influence contextual decision-making and prior experiences, therefore altering protective mechanisms. These findings underline how cognitive assessment and learning constitute the foundation of inducible defenses and emphasize their mental aspect.

A significant driver of ecological and evolutionary dynamics is phenotypic plasticity, an organism's ability to alter its traits in response to external stimuli [333,334]. This flexibility greatly increases the adaptation and longevity of organisms. Inducible defenses are a basic element under the predator–prey paradigm, maintaining the stability of populations and the organization of food webs [335–337].

There is strong evidence, thanks to empirical research, on how inducible defenses shape prey reactions. Riessen and Trevett-Smith, for example, created a hypothesis based on size-selective predation, subsequently confirmed by Daphnia tests where neck spines grow in the presence of Chaoborus larvae [338]. Further research with rotifers [339] and frog tadpoles [340,341] shows how visual or chemical predator signals shape the behavior of prey. Other studies indicate that frequent predator presence improves anti-predator responses in related prey species [342]. Several theoretical models have been constructed considering the limits of experimental methods in capturing the whole complexity of these interactions. Three frameworks, Fitness Gradient (FG), Optimal Trait (OT), and Switching Function (SF), were suggested by Yamamichi et al. to include inducible defenses in predator–prey dynamics [335]. While Sun et al. simulated anti-predator behavior activated only when the prey population surpasses a crucial threshold [343], Vos et al. assessed how inducible polymorphisms affected the stability of bi- and tri-trophic systems [344]. Under infection pressure, Liu and Liu investigated inducible protection in prey populations [345]; Ramos-Jiliberto et al. presented defense-modified functional response formulations to analyze system dynamics using numerical simulations [346]. Gonzá lez-Olivares et al. offered a conceptual categorization of prey defense mechanisms whereby predator biomass determines defense strength [347]. Using a metric $R = U_r/U$, defenses were classified based on resistant prey biomass denoted by U_r. Assuming $\partial R/\partial U = 0$, the model describes inducible defenses as reactions that grow with predator presence but not prey quantity.

All of these studies taken together show that although ecological in result, psychological processes in prey have a major impact on inducible defenses. They significantly influence predator–prey interactions, therefore influencing long-term evolutionary paths as well as instantaneous survival methods [348,349].

4.4. Cooperative Hunting

When aiming for big prey, cooperative hunting—also known as pack hunting—is a well-documented social behavior in which predators cooperate to increase foraging efficiency and hunting success [350]. Among the examples are coyotes feeding on mule deer, hyenas hunting gemsbok, and lions focusing on cape buffalo only under the backing of a particular social structure, a pride, or a family unit [351]. Likewise, bigger packs of African wild canines have shown better hunting efficiency than smaller groupings [350].

Usually, this kind of collaboration results from (i) a group effort producing common benefits and (ii) the advantages to every member exceeding personal expenses. This behavior is widespread in nature across many taxa, including wolves, wild canines, chimps, birds, ants, spiders, and even some marine life [352–354].

Reports of several kinds of collaboration, including predator inspection, group formation, cooperative breeding, combined hunting, and group defense, abound [211,355,356]. Mutual collaboration is also shown by symbiotic systems such as those between myc-

orrhizal fungi and plant species [211] or between deep-sea tubeworms and microbial symbionts [357].

Mathematical modeling has allowed one to investigate the dynamic and ecological effects of collaboration. Berec combined a Holling type II response with cooperative hunting into a Rosenzweig–MacArthur model [358]. Using a Lotka–Volterra-type model with cooperative hunting among predators, Alves and Hilker showed that such collaboration improves predator persistence [359]. Cooperation is expressed in these models by a modified encounter rate, e.g., $f(N, P) = (b + \alpha P)NP$, where α gauges the degree of cooperation, and N and P are the biomass of the prey and predator, respectively [360].

From lions [351] to wild chimpanzees [361,362] to hyenas [363] to different fish species [364,365] to reptiles [366] to arthropods like spiders [367,368] and heteropterans [369], cooperative hunting has been recorded in a great variety of species. Although the evolutionary roots of cooperative hunting are still unknown, some scientists argue that it might result from general social behavior rather than from the outcome of natural selection [356]. Recent studies by Pacher et al. show collective hunting behavior in striped marlin, therefore stressing how the mobility states of prey affect predator attack tactics [370]. Their research supports the idea of by-product mutualism, in which case predators gain individually from collective hunting without intentional cooperation, especially when prey schools are mobile and prone to fragmentation, hence improving predator success by better isolation of prey.

Cooperation is also clear in prey animals. For instance, mutualistic defenses arise on coral reefs between sea anemones and anemonefish [371], and buffalo herds in southern Africa gather to guard against lions [372]. Blue-tailed bee-eaters during the mating season also show evidence of avian cooperation [373]. There are a number of benefits to hunting in a group, including a lower risk of kleptoparasitism, faster prey capture rates, easier access to bigger game, and shorter pursuit times [374–377]. The variety and efficacy of cooperative techniques were highlighted by Packer and Ruttan's cataloging of 61 species' hunting strategies [356].

Mathematical research now covers the consequences of cooperative behavior on ecological levels as well as between species. For discrete-time predator–prey models, for example, cooperative hunting has been demonstrated to change the transition to chaos [378,379]; stage-structured prey models have included intra-species cooperation for defense [380]. Other studies have looked at how cooperative hunting is performed under delay effects and in concert with fear reactions [246–248]. Also, researchers have looked at predators' cooperative effects in discrete models [381] as well as spatio-temporal models as in [382,383].

Effective hunting is only one way that cooperating predators may influence their prey, and fear effects also play a role in it [267]. Elk, for example, alter their monitoring and feeding habits to stay away from regions frequented by wolves [384–387]. Similarly, lions have an effect on how giraffes and zebras move around in space [388–390]. Recent studies have started to investigate the coupled dynamics of fear and collaboration [247], which had previously been investigated independently inside mathematical models [209,358]. Cooperation in hunting has been the subject of further research in a number of settings, including spatio-temporal models [391], chemotaxis-driven systems [392], stage-structured populations [393], and predator–prey models with nonlocal interactions [394].

4.5. Herd Behavior

Herd behavior reduces individual susceptibility by means of collective defense, alertness, and confusion effects, therefore influencing predator–prey dynamics. Research on baboons mowing down predators and muskoxen establishing protective rings provides empirical evidence of the usefulness of social groups for predator avoidance [395–397].

Arditi and Ginzburg developed prey-dependent functional responses, in which predation depends just on prey density, to include such effects [398]. Ajraldi et al. suggested, however, that only prey on the group's periphery (proportional to $\sqrt{N}$, where N is total prey biomass) be vulnerable to predation in order to more fairly represent group defense systems [399]. Braza formalized this by adjusting the Holling type-II response as follows:

$$p(N) = \frac{c\sqrt{N}}{1 + T_h c\sqrt{N}}, \tag{23}$$

which incorporates spatial structure and catch reduced predation due to herding [400].

Later models have greatly expanded upon the fundamental knowledge of herd behavior in ecological systems. Many studies have shown that, along with diffusion, herd behavior may produce oscillatory or even chaotic dynamics [401,402]. Herding has been shown by Angulo et al. to help reduce Allee effects, hence stabilizing tiny populations [403]. More recent studies have incorporated both deterministic and stochastic dynamics, therefore extending these discoveries throughout a variety of modeling systems. Biswas et al. investigated herd harvesting in conjunction with density-dependent cross-diffusion, for example, to expose rich spatial patterns and complicated bifurcations [404]. Studying discrete Gompertz models with square-root functional responses, Ahmed and Almatrafi demonstrated how much predator death rates may influence system dynamics [405]. Alebraheem discovered in a stochastic setting that prey herd immigration guarantees persistence under environmental unpredictability and improves stability [406]. In the same vein, Javaid et al. connected bifurcation events and chaotic dynamics in discrete-time systems to herd behavior and Allee effects [407].

Numerous studies have looked into herding's spatial and cooperative factors as well. While Akanksha et al. looked at the role cooperative hunting and diffusion play in increasing population resilience [408], Pareek and Baghel examined how herd mobility affects predator success rates [409]. Peng et al. [410] and Peng and Li [411] investigated predator–prey systems with stage structure, time delays, and nonlocal competition, thereby revealing requirements for threshold-dependent stability and pointing the direction of double-Hopf bifurcations. To show their mutual impact on predator–prey dynamics, Saha and Samanta presented a predator–prey interaction with simultaneous fear effects and herd behavior of prey species [412]. Chen et al. also showed that under significant exploitation pressure, nonlinear harvesting combined with square-root responses might cause equilibrium shifts or possibly population collapse [413].

Research in this area has also come from computational and empirical sources. Bartashevich et al. looked at the 'fountain effect', a synchronized escape technique wherein prey divides and reassembles after a predator strikes [414]. They demonstrated how basic escape heuristics and social alignment norms may explain this strong behavioral reaction by means of drone video and agent-based modeling, therefore coupling predator attack direction with emerging collective escape forms. These studies agree generally that the stability, bifurcation structure, and spatial dynamics of predator–prey systems are mostly shaped by herd behavior, mathematically described by perimeter-based or square-root functional responses.

4.6. Anti-Predator Behavior

Originally modeled by the traditional Lotka–Volterra equations, the predator–prey interaction has been a fundamental subject in theoretical ecology [415–418]. Conventional wisdom usually holds that predators consume their victims without challenge. Real-world data, however, frequently run counter to this presumption, as prey species might either

fight or even damage their predators [419,420]. Known as anti-predator behavior, this interaction covers several tactics acquired by prey to prevent or discourage predation.

Anti-predator behavior consists of morphological changes and behavioral reactions. Some species, especially young ones, actively fight predators. While baleen whales (*Mysticeti*) use group defense methods against killer whales [421], mule deer (*O. hemionus*) have been recorded protecting conspecifics by attacking coyotes (*Canis latrans*) during predation events [422]. Such reactions underline the ability of the prey to directly affect predator dynamics.

Through ecological feedback networks, prey species sometimes indirectly influence predator numbers in certain habitats. In China's alpine meadow ecosystems, the plateau pika (*Ochotona curzoniae*) is absolutely vital; its overpopulation, caused by habitat destruction, lowers the plant cover [423–425]. On the other hand, increasing plant density has been seen to lower pika awareness, which increases the predation rates by natural predators such as owls [426]. Moreover, as efficient anti-predator signals in aposematic tactics, butterfly larvae adopt certain color patterns, such as horizontal bands and spots, thereby boosting predator avoidance via better conspicuousness and memorability [427]. This case shows how environmental factors could control anti-predator dynamics.

Generally speaking, anti-predator techniques fall into two categories: (i) direct attack by prey on predators [428–432], and (ii) physical or behavioral modifications to lower susceptibility [427,433–438]. The prey's behavior of avoiding predators is widely researched and acknowledged to significantly influence population shifts and environmental stability. These effects are heavily dependent on elements like memory, temporal delays, predator–prey interactions, and adaptive responses [269,271,346,439–443].

Ives and Dobson [439] modeled a predator–prey interaction with anti-predator behavior (through morphological changes):

$$\dot{N}(t) = \lambda N\left(1 - \frac{N}{k}\right) - \nu - \frac{e^{-\epsilon\nu} qNP}{1 + aN}, \quad \dot{P}(t) = \frac{ce^{-\epsilon\nu} qNP}{1 + aN} - mP, \tag{24}$$

where $N(t)$ and $P(t)$ represent prey and predator populations, and ν, ϵ denote the level and efficiency of anti-predator behavior. Stronger anti-predator behavior, according to their conclusions, lowers predation and improves prey survival by minimizing oscillatory dynamics.

Active defense systems in prey populations have been investigated in several models. Tang and Xiao showed that such actions can greatly slow down the evolution of predators by introducing a system whereby mature prey actively fight exposed predators [441]. Building on this, Sun et al. created a model whereby prey show anti-predator behavior just when their population reaches a crucial level [343]. Higher frequencies of such defensive reactions, according to their results, improve prey persistence and help to foster stable cohabitation with predators. KP and Kumar similarly investigated a stage-structured model with prey anti-predator behavior, especially aimed at young predators [285].

Taking a different tack, Klamser and Romanczuk concentrated on group predator avoidance in training prey [444]. Their spatially detailed model exposed that predator avoidance is most successful close to a key transition between disordered and organized group dynamics. Fascinatingly, emergent spatial self-organizing is responsible for this peak performance rather than individual response. They did, however, also observe that severe selection gradients cause this crucial condition to be evolutionarily unstable.

Apart from direct contacts, several studies underline the significant non-lethal influence predators have on the health and behavior of their victims [445]. Sometimes more powerful than direct attacks, the simple threat of predation can cause major changes. For example, salamanders lower their foraging activity in the presence of snakes [446]; yet,

snowshoe hares (*Lepus americanus*) suffer decreased reproductive success at high predation danger [447,448]. Furthermore, prey can pay energy and nutritional costs when they migrate to low-risk environments to escape predators [449]. In general, predator–prey dynamics are greatly shaped by both passive and vigorous anti-predator activity. Including these actions within ecological models offers a more reasonable framework for conceptualizing population stability and persistence.

4.7. Group Defense

Understanding predator–prey dynamics depends critically on the functional response, i.e., the rate at which a predator takes in prey per unit time. Classical formulations, including the Holling-type functional responses (Types I, II, and III) [450], assume that the consumption rate monotonically rises with prey density. Empirical data, however, indicate that this presumption is not always true, especially in cases when prey display collective defense mechanisms.

Group defense is the decrease in predation efficiency triggered by the collective behavior of prey at larger densities. Ecological research has extensively recorded this phenomenon [302,397,451–453]. For instance, musk oxen show strong herd behavior that deters wolves, and attacks on solitary individuals are usually successful, whereas huge herds stay mostly unharmed [396,454]. Insect swarms also exhibit similar protective behaviors whereby predators battle to recognize and seize members of dense groupings [455–457]. Emphasizing the need for emotional states, diverse strategic planning, and nonlinear social interactions, Bellomo et al. suggested a multi-scale modeling paradigm for behavioral human crowds. Their approach of 'activity' as a dynamic behavioral variable provides insightful analysis of group-level reactions molded by individual psychological qualities, therefore matching group defense mechanisms in ecological systems [458].

Filamentous algae have been proven to disrupt zooplankton's feeding systems in aquatic environments. According to Dawidowicz et al., Daphnia can eat these algae in low quantities, but at greater concentrations, the algae jam their filtering machinery [459]. Furthermore, certain phytoplankton species produce poisonous molecules that discourage zooplankton feeding, therefore acting as a chemical type of group defense [460,461].

Some other functional responses have been suggested to capture such non-monotonic predator–prey interactions. Andrews proposed the Monod–Haldane functional response $\phi(x) = mx/(x^2 + bx + a)$, which at low prey densities resembles the Michaelis–Menten (or Monod) form but contains an inhibitory effect at large densities [462]. Sugie and Howell developed a simpler variation $\phi(x) = x/(bx^2 + m)$, where $b = 1/i$, and i denotes the intensity of the inhibitory effect [463].

The Type-IV functional response, which models the decline in zooplankton feeding at high phytoplankton concentrations resulting from toxicity or interference, has a similar architecture:

$$\phi(x) = \frac{x}{\frac{x^2}{i} + x + m}, \tag{25}$$

where m denotes baseline consumption in the absence of inhibition, and i quantifies the inhibitory effect [460,464]. Especially for big values of i, the response lowers to the Holling Type-II form.

Group defense strategies incorporated into predator–prey models have attracted a lot of interest lately. Freedman et al. were among the first to formally model the impact [465]. Additional developments have added structural and geographical presumptions; for instance, Ajraldi et al. developed nonlinear interaction terms, i.e., the square root of population density, to capture interactions along population borders [399]. Recent research on the consequences of group defense and non-monotonic responses in ecological dynam-

ics underlines their relevance in producing more realistic and strong models of species interactions [285,400,466–472].

4.8. Population Dispersal/Migration

Wide-ranging psychological and ecological effects of population movement and dispersion have been investigated across many fields in both ecology and psychology. Particularly, migration may have strong psychological effects on people, families, and societies. The departure from familiar settings, such as home, social networks, and cultural backgrounds, frequently causes mental anguish, worry, and tension [473,474]. Combined with concerns about personal safety and future uncertainty, migrants regularly have great difficulty adjusting to new languages, cultures, and social conventions [475,476]. Many migrations, resulting from armed conflicts, economic collapse, or natural disasters, have forced elements that exacerbate emotional reactions like trauma, loss, and grief [477,478]. The migrant's attempt to create identification and belonging in strange surroundings shapes these psychological reactions even more [479,480]. Prejudice, linguistic obstacles, and difficulties with cultural identity might all lower immigrants' mental health and self-esteem [481–483]. Particularly for people who move without any family links or social networks, feelings of social isolation and loneliness are very prevalent [484]. Family separation can bring extra stress and disturb existing family dynamics, particularly involving dependent children or elderly relatives, hence generating intergenerational friction and changes in family roles. Still, many immigrants show great resiliency and hope, using cultural legacy, social ties, and personal advantages to negotiate these challenges [485]. Usually, the availability of inclusive support structures, easily available resources, and chances for meaningful social participation mediates their psychological adaptation and well-being [486,487]. Though tough, migration may also encourage personal development, empathy, and adaptation as people negotiate and overcome the obstacles of reconstructing life in a different setting [488–490]. Individual characteristics, contextual elements, and more general structural influences define the psychological effects of migration overall; so, successful addressing of migrant mental health depends on culturally responsive support structures that foster social inclusion [491].

Concurrent with this, ecological research has looked at how species move about and what it means for population growth and decline. Biotic interactions, spatial diversity, and dispersion patterns all affect how various species are distributed over landscapes [492–496]. Especially at the size of ecological patches, localized interactions between organisms and their surroundings can result in spatial self-organization [497,498]. Essential elements in the formation of such spatial structure have been shown to include limited dispersion ability and the consequent dispersal patterns [499–502].

In predator–prey systems, stimulus originating from prey usually shapes the non-random dispersion behavior of predators. This covers spatial fluctuation in prey density and signs of prey contact [503,504]. For instance, although mosquitoes are drawn from a distance by host smells [505–507], blood-feeding insects such as tsetse flies (*Glossina* spp.) create 'following swarms' in response to visual and olfactory signals from grazing ungulates [508,509]. The wood wasp Sirex noctilio responds to different host smell concentrations [507,510]; social insects like ants use pheromone trails to coordinate hunting activity [511]. By use of gustatory cues, plant-feeding insects also identify host plants [512,513]. In places with plenty of prey, these sensory-driven, non-random behaviors might generate increased predation rates, i.e., density-dependent predation, so controlling both prey and predator populations. Experimental work on immobile aphids and their predator coccinellids by [514] revealed that predator movement results from a combination of passive diffusion, conspecific attraction, and retention on prey-rich plants, demonstrating

that such predation helps to spatially self-organize aphid colonies. Japanese beetles exhibit similar patterns in response to feeding-induced plant volatiles [515]. These realizations inspire the development of a two-patch predator–prey model to examine the ecological effects of non-random predator foraging behavior motivated by prey interaction strength.

The prey (N_i) and predator (P_i) population dynamics across n geographical patches are presented here:

$$\begin{cases} \dfrac{dN_i}{dt} = f(N_i, P_i) + \displaystyle\sum_{j=1}^{n} D_{ij}^{N}(N_j - N_i), \\ \dfrac{dP_i}{dt} = g(N_i, P_i) + \displaystyle\sum_{j=1}^{n} D_{ij}^{P}(P_j - P_i) \end{cases} \tag{26}$$

where $f(N_i, P_i)$ and $g(N_i, P_i)$ represent the local predator–prey dynamics (e.g., Lotka–Volterra, Holling type II, etc.); D_{ij}^{N} and D_{ij}^{P} are the dispersal rates of prey and predators from patch j to i, respectively. Mathematical ecology has extensively explored the dynamics of predator–prey interactions in patchy environments [493,516–525]; a thorough survey is given in [526]. Many times, these investigations look at how patch interactions affect local population oscillation stability and synchronization [527,528]. Of note, [528,529] showed that spatial heterogeneities generated even by density-independent dispersion might stabilize prey distribution via self-organized dynamics.

Nevertheless, given their complexity, models including nonlinear or density-dependent dispersion behavior, especially those reflecting predator feeding strategies, remain very constrained [504]. Notable exceptions include models including predator attraction to prey [530], to conspecifics [531], or to locations with a high prey concentration [532,533]. In their fundamental work, [504] developed a mechanistic PDE model showing that area-restricted search behavior resulted in predator aggregation, in line with empirical observations from systems including blackbirds and coccinellids. Using a two-patch Rosenzweig–MacArthur model, [530] expanded the Holling time budget framework to construct nonlinear migration terms demonstrating that system dynamics are much influenced by foraging parameters. Analogous to this, [534] revealed the significance of dispersal rate and handling time by including density-independent prey migration and density-dependent predator dispersal. Another study, [535], investigated directed dispersal in which both prey and predators travel toward patches with greater fitness, showing that such movement cannot disrupt locally stable equilibria.

Building on this, [536] put out a hypothesis in which the intensity of predator–prey interaction directly drives predator dispersal. Their formulation fits several insect infrastructures, including aphids and coccinellids, and Japanese beetles with their host plants. Field studies reveal, for example, that Colorado potato beetles are drawn to previously uninfested potato plants only following conspecific larvae, hence underscoring the function of interaction-driven attraction [537]. The experimental results of [514] confirm this behavior even more since predator aggregation is highly connected with predator–prey interaction intensity. In their proposed model, predator dispersal between patches is governed by the term $\frac{b_j N_j P_j}{1+b_j h_j N_j}$, which captures the predator–prey interaction strength in patch j. Predators from patch i to patch j have a net dispersal given by the following equation:

$$\psi(N_i, P_i, N_j, P_j) = \frac{b_j N_j P_j}{1 + b_j h_j N_j}\rho_{ij} P_j - \frac{b_i N_i P_i}{1 + b_i h_i N_i}\rho_{ji} P_i \tag{27}$$

where ρ_{ij} denotes the dispersal constant from patch j to patch i. Supported by a large spectrum of field investigations on predator foraging behavior, this method represents reality's assertion that predator movement is stimulus-driven and directionally biased, i.e., $\rho_{ij} \neq \rho_{ji}$ [503,514].

The structure of predator–prey dynamics depends deeply on population distribution. Models by Kang et al., Xiao et al., and Gao et al. highlight how predator or prey movement, especially when non-random, nonlinear, or asymmetric, depending on patch quality and interaction strength, may promote stability, extinction, or coexistence [536,538,539]. Under Allee effects or disease pressure, Lu et al. and Yousif & Al-Husseiny show how environmental changes and migration affect regime transitions and system stability [540,541]. Sen et al. and Mondal et al. show that rich dynamical results, including synchronization, chaos, and multistability, may be obtained by dispersion mixed with cross-predation [542,543]. Furthermore, ref. [544] demonstrated how, in spatially expanded habitats, dispersal may result in a viable population in an area provided the amplitude of environmental variations is below an extinction threshold. These investigations taken together highlight dispersion as a fundamental process underlying spatial population control and ecological persistence.

4.9. Prey Switching by Looking for Alternative Food Sources

A fundamental adaptive foraging tactic, prey swapping helps predators maximize energy acquisition and survive under changing prey supply. Especially in generalist predators, functional responses, including switching behavior, greatly affect predator–prey dynamics by stabilizing oscillations and maintaining species coexistence [264,545–548]. Murdoch experimentally showed in a system including mussels, snails, and barnacles that switching enhances prey cohabitation [546]. Later, Tansky offered mathematical confirmation showing Volterra-type oscillations when prey have identical intrinsic rates of growth [548].

Theoretical models now include prey switching to include aspects such as environmental volatility, predator choice, and prey vulnerability. Garrott et al. modeled wolf–elk–bison dynamics, for example, and discovered that predator–prey interactions may be stabilized by prey flipping depending on abundance and vulnerability [549]. Extending this by integrating fear effects, Sahoo et al. demonstrated how perceived predation danger and prey quality may affect switching behavior and therefore support system stability [264]. Saha and Samanta arrived at similar results in two-prey–one-predator [550] and two-prey–two-predator systems [551] as well. Another possible stabilizing mechanism has been investigated as an alternative food supply. Further, food quality, amount, and seasonality may control asymptotic behavior and increase predator persistence, according to Srinivasus et al. [552] and Sahoo and Poria [553]. When coupled with fear effects and temporal delays, another often disregarded element, intraspecific rivalry among predators, has also been demonstrated to promote long-term cohabitation [554].

Prey switching motivated by prey abundance, vulnerability, seasonal availability, and predator status is repeatedly shown by empirical research spanning terrestrial and marine environments. Prey vulnerability, more than availability [555], seasonal dynamics [556], energy stress [557], and pack size [558] shape prey switching in wolf populations. Arctic foxes have been seen engaging in similar actions in changing their diet between stored food, microtines, and bird eggs based on availability and breeding seasons [559,560]. Among seabirds, changing environmental circumstances cause prey to change between fish species and sites, thereby influencing reproductive success and ecological effects [561–564]. Kuepfer et al. noted, however, that prey switching by albatrosses to fisheries discards did not reduce the demographic costs of poor natural foraging circumstances, therefore demonstrating that switching is not always adequate to counterbalance ecological stresses [565]. With behavioral patterns in prey commonly matching terrestrial and marine habitats, this cross-ecosystem consistency in predator foraging adaptations emphasizes the universality of prey switching as a regulatory mechanism [257]. Though the data is conflicting regarding sequential prey depletion as a motivator [566,567], marine animals also show switching

behavior; killer whales in the North Atlantic alternate between seals and herring depending on availability [568]. While red foxes go after deer fawns at vole lows [569], lynx, as terrestrial predators, go from snowshoe hares to caribou calves during hare population declines [570]. In response to herbivorous migration, lions and cheetahs change the food they choose seasonally [571]; invasive lionfish show density-dependent switching that could help to minimize ecological disturbance [572]. Copepods and true bugs like Macrolophus pygmaeus have also shown shifting behavior that improves energy acquisition and pest control efficiency [573,574].

Mathematical contributions also support the prey switching behavior. Emphasizing the part played by energy trade-offs and ecological restrictions, Prokopenko et al. [575] and Idmbarek et al. [576] relate switching to optimum foraging theory and utility maximizing theory. By demonstrating negative frequency-dependent selection in wolves, Hoy et al. provide subtlety that challenges conventional switching theories [577]. When the main prey is scarce, other food sources become very crucial. Especially under coarse-grained environmental settings, Van Baalen et al. demonstrated that switching to constant-density alternative food may buffer predators and lower prey population fluctuations [578]. Although these kinds of changes may not completely stabilize equilibria, they usually help to avert species extinction and prolong system persistence. Wolf and Ripple observe in conservation settings that prey depletion leads predators to migrate to inferior or human-associated food sources, therefore generating questions regarding nutritional stress, range changes, and conflict [579]. In the end, we can say that prey switching, especially toward other food sources, is a common and flexible tactic that improves energy optimization and stabilizes predator–prey dynamics. Its manifestation affects ecosystem stability, wildlife management, and conservation in general, depending on ecological, behavioral, and physiological elements.

From collective behaviors like herd movement and cooperative hunting to fear-induced dynamics and inducible defenses, the integration of psychological and behavioral responses into predator–prey models gives a deeper, more realistic picture of ecological interactions. These elements not only define the instantaneous survival strategies of species but also affect long-term population dynamics, regional patterns, and ecosystem stability, therefore underlining the requirement of behaviorally informed ecological modeling.

Beyond what conventional models estimate, the investigation of psychological impacts in predator–prey dynamics exposes how individual and group behavioral adaptations may radically alter ecological consequences. These results highlight the significance of including emotional and cognitive aspects in ecological modeling systems. Examining how psychological elements similarly impact the dynamics of disease propagation becomes essential given the similarities between ecological and epidemiological systems, both controlled by interactions, feedback loops, and behavioral responses. Building on this comparison, we now focus on epidemiological modeling in the following part, where knowledge of human behavior, perspective of risk, and decision-making procedures become equally important in forecasting and controlling infectious disease epidemics.

5. Psychological Effects in Epidemiological Modeling

It is becoming more and more clear that understanding how people and groups react to outbreaks of infectious diseases is an important part of making epidemiological models better and more accurate [580]. The SIR and SEIR paradigms, two conventional approaches to epidemiology, have placed a heavy emphasis on the dynamics of biological transmission for quite some time. But behavior by individuals during health emergencies brings variation that simple biology models sometimes overlook. Transmission paths and intervention efficacy are substantially influenced by risk perception, emotional reactions,

patterns of social contact, and adaptive behavior. Consequently, an increasing amount of multidisciplinary research underlines the need to include psychological and behavioral aspects in epidemic models to improve their prediction ability and policy relevance.

- Psychological inhibition and modified incidence rates: People generally respond to epidemic problems by making psychological changes that help them avoid contact with others and stop the spread of the disease [581–583]. These modifications, which range from social disengagement to improved hygiene, necessitate adjustments to the normal bilinear incidence rates, typically represented as $f(S, I) = kSI$ in SIR/SEIR models [584–589]. Subsequently, epidemiological studies utilized a nonlinear incidence rate [590–594]. Capasso and Serio proposed a saturated incidence rate to reflect behavioral inhibition [595]:

$$f(S, I) = \frac{kSI}{1 + \epsilon I}, \tag{28}$$

  where k and ϵ are constants, kI measures the infection force, and $1/(1 + \epsilon I)$ reflects the reduction in contact due to psychological inhibition as infection prevalence increases [583,596]. This functional form is mostly phenomenological, despite its widespread use in classical epidemic modeling. Its empirical validation is largely derived from initial short-term outbreak findings, and its repeatability across diverse populations or long-term behavioral responses is still constrained. So, even if it does a good job of capturing monotonic behavioral inhibition, its generalizability is limited by how simple its assumptions are. This was further generalized to nonmonotonic forms, such as $f(S, I) = kSI^p/(1 + \epsilon I^q)$ [597], capturing the 'psychological effect' in response to infection prevalence. Nonetheless, numerous extensions depend predominantly on simulation-based validation and are deficient in extensive empirical calibration. Consequently, the scope and duration of the inferred psychological effects exhibit significant variability across research, and their consistency across other disorders or temporal intervals are yet to be definitively determined. Subsequent research elucidates the impact of psychological inhibition on illness suppression by including information-induced behavioral alteration [598] and optimal control strategies, such as social distancing and heightened awareness [599]. These models have conceptual viability; nevertheless, as to previous formulations, their behavioral elements are predominantly substantiated through theoretical frameworks rather than replicated empirical datasets, hence constraining their resilience.
- Network topology, crowding effects, and behavioral feedback: Other types of studies have looked at how the structure of a network influences how people act and how information spreads [600–604]. Research on business and communication networks shows that topological features like connectivity and clustering affect how users operate and how viruses spread. In particular, crowding effects in point-to-group (P2G) network sharing might inhibit the transmission of viruses by causing delays and withdrawal behavior when people feel threatened [605]. It is important to note that many of these behavioral consequences are only replicated under certain or idealized network assumptions, which makes it unclear how well they apply to real-world systems that are not homogeneous [606]. Controlling a virus depends extensively on psychological factors, such as disconnecting from infected nodes [607]. Using a modified incidence rate, Yuan et al. created a nonlinear e-SEIR model including crowding and behavioral inhibition [608]:

$$f(S, E, I) = \frac{\beta SE}{1 + \epsilon I^p}, \ (p \geq 0), \tag{29}$$

thereby integrating user connectivity to psychological feedback. Here, βSE captures virus transmission influenced by user connectivity, and $1/(1+\epsilon I^p)$ reflects psychological inhibition as infections rise. Behavioral inhibition increases with the number of infectives and is influenced by network-driven exposure patterns. This model's behavioral modulation is closely linked to network structure, which makes its predictions very sensitive to assumptions about topology and how users interact with each other. This is different from the standard saturated incidence form. Its validation relies predominantly on simulations, and evidence supporting its replication outside of stylized networks is still scarce.

Bellomo et al. proposed a multi-scale modeling framework for behavioral human crowds, underscoring the necessity of emotional states, varied strategic planning, and nonlinear social interactions [458]. Their incorporation of 'activity' as a dynamic behavioral variable facilitates a nuanced examination of group-level responses shaped by individual psychological traits, augmenting the understanding of crowd-mediated behavioral feedback during epidemics. Similarly, a fractional-order SIRS model incorporating memory-driven vaccination behavior captures nonlinear reactions to public health communications [609]. Network-level behavioral interactions and awareness of HIV preventive methods, such as PrEP, similarly influence epidemic patterns [610]. These differences reveal that both formulations in (28) and (29) represent psychological inhibition, but they are very different in terms of their assumptions, scope, and evidence. The standard saturated incidence is more ideal for uniform population-level behavioral responses, while the network-based formulation is preferable when connection and exposure structure predominate behavioral adaptations. This comparative framework helps make it clear when one model is right and also where further empirical reproducibility is needed.

- Emotional distress and public compliance: Public cooperation with health treatments is extensively shaped by emotional reactions during epidemics, including dread, worry, and depression. Growing empirical studies show an increase in psychological suffering during infectious outbreaks, disproportionately affecting those with low socioeconomic levels [611–619]. These emotional states might compromise public health policies, lead to avoidance behaviors, disseminate false information, or even result in panic-driven decision-making.

  Media coverage sometimes magnifies these dynamics by raising perceived threats, which could then enhance maladaptive behavior reactions. For instance, Taylor et al. discovered during Australia's equine influenza epidemic that financial uncertainty was strongly correlated with emotional stress, therefore illustrating how structural vulnerabilities impact psychological effects [612]. Socioeconomic level also influences coping strategies like hope for recovery or faith in organizations. Studies by Zhou et al., Li et al., and Vázquez et al. validate that these emotional elements, especially optimism and trust, act as moderating variables that may either buffer psychological stress or magnify its impact under uncertainty [615,617,619].

  Carbonaro and Serra [121] presented a model reflecting the stochastic evolution of emotional states, including anxiety and reliability, over time-dependent interpersonal encounters, thereby capturing such dynamics quantitatively. The model characterizes the probability $\pi ij(x,t)$ of a certain emotional state shared across persons i and j developing via the following equation:

$$\frac{\partial \pi ij(x,t)}{\partial t} = \mathbf{G}(\pi ij) - \mathbf{L}(\pi_{ij}), \tag{30}$$

where $\mathbf{G}(\pi ij)$ and $\mathbf{L}(\pi_{ij})$ represent gain and loss terms influenced by both self-reflection and emotional contagion through social networks. This formulation corresponds with expansions of behavioral SIR models, in which emotional dynamics interact with epidemiological states to enable researchers to predict adaptive behavioral transitions such as risk denial, greater compliance, or panic-induced withdrawal. Including such emotion-specific processes into disease modeling algorithms helps one to better grasp how psychological elements affect epidemic paths, particularly in times of crisis that test public health infrastructure and collective emotional resilience.

- Behavioral adaptation and disease transmission: Essential to epidemic outcomes and influenced by psychological elements like anxiety, unpredictability, exhaustion, and compliance to social norms are behavioral reactions that include social distance, hand cleanliness, and restricted mobility [599,610,620–653]. Behavioral changes like panic purchasing, broad mask usage, remote working, and altered travel patterns were clearly seen during the COVID-19 epidemic. Though first successful, these adaptive activities often fade with time from habituation or tiredness [654–669]. Trust in authority and social conventions mediates these actions; tiredness may cause them to fade over time [670–674]. Using fractional derivatives [609], transitions between immune and non-immune susceptibles depending on past exposure [675], and time-dependent vaccination and distancing approaches [676], models including memory-driven alterations in vaccination attitudes describe behavioral adaptability. These strategies draw attention to how adaptive feedback shapes the course of an epidemic.
- Migration restrictions and their psychological effects: Recommended responses to epidemic challenges include migration controls like lockdowns, quarantines, and travel bans, but they also have major psychological effects. Public confidence and obedience may be undermined by fear, solitude, and financial stress linked with these regulations [227,677–679]. Several research studies show that a lack of accessibility and insufficient communication aggravate these consequences, hence lowering the effectiveness of mobility limitations. Mathematical models sometimes show such constraints as control variables controlling isolation or social distance. Researchers have worked on models, for example, that limit movement through the variables signaling remoteness and isolation rather than geographical restrictions [599,609,680,681]. These depictions help one understand how public perceptions and legislative stringency interact to affect results. Trust in authority and clear communication define public adherence most of all; contradictory communication reduces compliance [682–685].
- Advances in behaviorally informed modeling: Recent advances in epidemiological modeling have progressively recognized how closely disease dynamics are shaped by emotional contagion and behavioral feedback. Compartmental models are often lacking in reflecting these intricate psychological dynamics. Bedson et al. underline the shortcomings of traditional models by means of a thorough evaluation of approaches that include psychological aspects in epidemic models, therefore supporting more complex behavioral representations [686]. One important example of this kind of progress is the prevalence-elastic behavior model, which holds that people change their social distance or vaccine intake in response to imagined illness risks [687]. Building on this, Dutta et al. show how to simulate long-memory behavioral effects using fractional calculus, hence allowing the capturing of continuous individual responses throughout time [609]. In companion work, Dutta et al. and Saha et al. include immunological variability, optimum vaccination techniques, and dynamic feedback mechanisms, including adaptive social distance, therefore offering more realistic representations of behavioral development during epidemics [675,676].

Coupled contagion models improve our knowledge substantially as they concurrently represent the transmission of transmissible diseases and anxiety. Studies by Funk et al. and Epstein et al. have demonstrated that these systems may produce intricate dynamics, including oscillating epidemic patterns [688,689]. Particularly, Agent_Zero, an agent-based model (ABM), shows a major advance in this respect. These models provide a detailed picture of behavioral variety by simulating diverse creatures whose decisions are shaped by cognitive, emotional, and social stimuli [690]. Further improving the relevance of these models is the growing availability of real-time behavioral data and qualitative insights from risk communication and community involvement (RCCE) approaches. Infection paths are much shaped by social and psychological elements, including individual vulnerability, patterns of social mixing, and public activity engagement. Emphasizing the part of behaviorally driven variation in epidemic dissemination, ABMs have revealed how psychosocial interactions dramatically affect asymptomatic transmission patterns in COVID-19 [691].

Gigerenzer's idea of psychological AI also brings heuristic-based methods that give human judgment under ambiguity top priority. His criticism of data-centric epidemic forecasting systems such as Google Flu Trends emphasizes the need for psychological heuristics, such as the recency effect, which, in some situations, can beat more intricate prediction algorithms [692]. These results highlight the need to include limited rationality and psychological realism into epidemic models to improve their predictive and explanatory capacity.

- Psychoneuroimmunological insights: A key assumption of psychoneuroimmunology (PNI) is that psychological moods and immunological function have a complicated, bidirectional interaction. Depression, anxiety, and chronic stress are among the mental health disorders most linked to aggravation of inflammatory diseases, including inflammatory bowel disease (IBD), via the gut–brain axis and vagal tone changes [693–695]. Results from animal models also confirm this link; for example, experimentally induced psychological discomfort has been found to disturb gut flora and decrease immune function, therefore highlighting physiologically ingrained routes by which emotions affect immunological resistance [696,697].

  These revelations are now included in models of epidemiology. Dutta et al. use fractional-order models, for instance, to capture memory-dependent behavioral reactions like vaccination reluctance, therefore illustrating how cognitive biases and belief systems directly affect immunological risk via behavioral paths [609]. Models of HIV control show a similar junction of psychological and immunological processes whereby cognitive assessment of risk and informational awareness shape the intake of pre-exposure prophylaxis (PrEP), therefore tying emotional states to population-level disease resistance [610]. Further extending this integration, Lv et al. suggest an enhanced SIRS framework including psychological variation among people. Under this approach, the population is split into level-headed and impatient groups to reflect differences in behavioral responsiveness during public crises [698]. Dynamic psychological interactions bridge ideas from personality psychology and conventional epidemiology to simulate emotional contagion, much as infectious disease transmission is modeled. This formulation offers a convincing structure for modeling panic spread and its influence on epidemic dynamics. These models, taken together, highlight the requirement of epidemiological methods that consider the interactions among psychological features, emotional reactions, and immunological results. Such integration improves the forecasting power of models under actual psychosocial settings and provides a more complete knowledge of population health.

The amalgamation of psychological and behavioral elements into epidemic modeling is not only necessary but also helps to precisely predict disease dynamics and guide the development of successful treatments. From nonlinear incidence rates and network-informed behaviors to emotional discomfort and adaptive compliance, these factors transform both theoretical models and useful policy instruments. The growing sophistication of the discipline is shown by advances in fractional calculus, agent-based simulations, and linked contagion models. Public health preparation and response depend critically on models reflecting the whole spectrum of human reaction as epidemics progressively develop in psychologically sensitive and socially complex environments.

As we show in this part, the inclusion of psychological dynamics into epidemiological models has consistently greatly improved our knowledge of how panic, perception, and behavioral actions affect the transmission and control of infectious illnesses. These models highlight how basic components in projecting public health outcomes should include cognitive and emotional considerations. This focus on human psychology as a fundamental driver of system dynamics naturally extends to complicated fields where human behavior interacts with technology or computational processes. Thus, the next part explores psychological consequences in the domains of sophisticated systems, AI, and advanced technologies. It investigates how cognitive biases, emotional states, and decision-making heuristics affect human–AI interactions, autonomous systems, and emergent behaviors in sociotechnical networks.

6. Psychological Effects in Advanced Technology, AI, and Complex Systems

The junction of psychology and AI has created fresh paths for investigating how sophisticated technology could both influence and reflect human emotional and cognitive processes. Far from being passive tools, AI systems interact with, adapt to, and influence human users, therefore behaving as psychologically active agents.

Through events like algorithm aversion, perceived injustice, and lower confidence in automated systems, Williams and Lim underline how AI may affect users' emotional states, cognitive biases, and actions [699]. From a cognitive modeling standpoint, Bayesian and probabilistic models provide effective means of including uncertainty management and inductive reasoning into AI systems [700]. By helping machine learning match human-like conceptual comprehension, these models help to close the psychological distance between people and computers.

Affective computing has emerged as a key component in developing emotionally aware AI. Deep learning algorithms for affect detection and posture estimation have shown outstanding ability to capture subtle emotional cues, thereby boosting the quality of human–computer interaction [701,702]. Probabilistic affective user models, such as those based on OCC appraisal theory, employ dynamic Bayesian networks to adapt to users' changing emotions in scenarios like education and social interaction [703,704].

Proposing a Bayesian generalization of Affect Control Theory (BayesACT), Schröder et al. extend this integration by framing identities as probabilistically moving entities inside emotionally charged social settings [705]. This is consistent with Kaplan's Dynamic Systems Model of Role Identity, where identity arises from nonlinear, context-dependent interactions—a concept that is gaining important in the study of human–AI dynamics [706].

Psychological modeling also helps AI systems also to exhibit strategic behavior. By considering human-bounded intelligence and noisy reasoning, Zhu et al. and Hartford et al. demonstrate that deep learning models can outperform conventional game-theoretic techniques [707,708]. Fintz et al. improve interpretability by merging deep networks for predicting accuracy with cognitive models for post hoc explanation in human decision-making tasks [709].

Emotion modeling has been broadened in reinforcement learning. Zhang et al. use appraisal theory with reinforcement learning to mimic changing emotional states, allowing systems to predict user responses such as happiness or annoyance [104]. Similarly, Jupalle et al. show that machine learning classifiers can reliably recognize emotional behaviors from multimodal speech and gesture data, with potential applications in healthcare and digital platforms [710]. Zhou et al. use deep reinforcement learning to recognize complicated behavioral feedback in healthcare [711], whereas Raina et al. demonstrate how deep models may mimic innovative human problem-solving tactics, allowing human–AI collaboration in open-ended tasks [712].

The tendency is toward a new generation of AI that simulates human emotion, reasoning, and adaptive behavior rather than just mechanical input–output transformations. Cognitive psychology and emotional neuroscience are rapidly being included in AI designs to improve transparency, adaptability, and real-world use.

However, classic brain-inspired models frequently fail to capture the emotional volatility and subjective experiences that constitute human cognition. Zador [713] and Shi et al. [714] disagree with solely algorithmic simulations, highlighting their shortcomings. While most of modern AI development is still based on biologically inspired cognitive architectures and neural networks [715], these models frequently neglect the dynamics of changing mental and emotional states. Cognitive psychology, which includes concepts like attention, motivation, and emotion, offers a more complex framework for adaptive decision-making and learning under ambiguity [172,716–718]. These challenges become even more pronounced with the emergence of large language models, whose impressive linguistic capabilities often mask deeper limitations in cognitive representation.

Zhang et al. argue that, despite their outstanding linguistic performance, large language models (LLMs) lack the conceptual depth and abstraction required for human mathematical reasoning [719]. They argue for AI systems founded on cognitive psychology concepts such as conceptual-role semantics, metacognition, and the approximation number system. These abilities allow humans to generalize effectively and reason counterfactually, capacities that most AI currently lacks.

Minsky's 'society of mind' model, which urged incorporating psychological and developmental ideas into AI creation, foresaw many of these problems [720,721]. Rabinowitz et al. extend this legacy by adding AI systems capable of theory of mind, hence enabling inference of others' beliefs and intentions [722]. Ritter et al. show that cognitive biases similar to human perception may be displayed in visual reasoning networks [723]. Likewise, the Japanese framework of "Kansei Engineering" and Wang's "artificial psychology" combine sensory and emotional reactions into design systems [724].

The stochastic framework of Carbonaro and Serra [121] offers one important addition as it quantitatively quantifies emotional interactions using probabilistic distributions. In particular, the predicted emotional state the agent i attributes to their interaction with the agent j at the time t is provided by the following equation:

$$\mathbb{E}[u_{ij}(t)] = \int x \pi_{ij}(x,t) dx, \tag{31}$$

where $u_{ij}(t)$ is a random variable encoding the emotional value by the agent i of their relationship with agent j, and x shows a probable realization of this emotional state. The probability density function (PDF) characterizing the distribution of emotional states quantifies the likelihood that the emotion felt by agent i toward agent j assumes the value x at time π_{ij}. This stochastic formalism offers a moral basis for creating adaptive, emotion-aware AI systems proficient in simulating complex interpersonal dynamics.

The integration of cognitive and affective models into AI does not remain theoretical; it has led to numerous practical systems grounded in psychological science. Psychological ideas have been integrated with AI to produce transformative uses in many fields where cognitive understanding and emotion-specific modeling greatly improve system performance and human alignment. These applications span perceptual, affective, and creative domains, including the following:

(i) Facial attractiveness and visual psychology: Deep learning architectures like AlexNet and ResNet, trained on datasets like SCUT-FBP5500, have efficiently represented human impressions of face aesthetics molded by consistent psychological preferences across age, culture, and gender [725–727]. Combining local and global face characteristics with multi-task learning helps Vahdati et al. increase prediction accuracy [728]. Meta-learning techniques have been used to personalize elegance evaluation and dynamically adjust to user-specific aesthetic choices, hence addressing individual variance [729–733].

(ii) Affective computing and emotion recognition: Originally put up by Picard, affective computing recognizes the importance of emotion in intelligent behavior from a viewpoint compatible with Simon's claim that cognition is incomplete without affect [734,735]. Bechara et al. have shown that deficits in emotional-processing brain areas compromise decision-making even in cases with logical thinking intact [736]. Emotion identification systems depend more and more on multimodal data, including speech characteristics [737], facial action units (e.g., FACS) [738,739], and EEG signals [740,741]. Liu et al. suggested a spatio-temporal convolution attention neural network (3DCANN) leveraging dual attention processes to show better classification performance over many channels and time frames for EEG-based emotion identification [742]. In a similar vein, Cheng et al. presented MSDCGTNet, a new multi-scale CNN and gated transformer-based model that allows accurate and effective emotional state identification throughout several benchmark datasets [743]. Effective temporal emotional signals in speech-based systems are captured by deep learning models, including LSTM and the upgraded BLSTM-DSA architecture [744,745]. With depression diagnosis systems combining BP neural networks and Adaboost algorithms reaching over 81% accuracy, multimodal approaches integrating voice and facial expression have also demonstrated great efficacy in mental health diagnoses [746]. Hernández-Marcos and Ros suggested a self-learning emotional framework for AI agents based on reinforcement learning ideas, hence extending this trend [747]. Their approach shows congruence with natural emotional patterns and develops synthetic feelings by means of the temporal dynamics of reward-based variables.

(iii) Music, emotion, and psychological regulation: An essentially emotional medium with great regulating power is music. AI-based music systems are now able to analyze and modify musical output in real time to reflect or impact a user's emotive state are. Showing statistically substantial categorization accuracy of emotional states, Affective Brain-Computer Music Intervals (aBCMI) use EEG inputs to identify arousal and valence levels and change music accordingly [748,749]. Strong connections between auditory stimuli and emotional responses throughout cortical and limbic networks help EEG-based studies to support these systems [750]. Today, EEG-based functional connectivity during emotional experience has attracted significant attention. Moreover, as pointed out in [751] and references therein, EEG evidence consistently reveals shared neural mechanisms between affect and cognition, overlapping anatomical substrates, and coordinated temporal dynamics between emotional and cognitive processes. This underscores the need to develop unified mathematical models that preserve insights from specialized research while capturing the holistic nature of men-

tal function. It is expected that such models will assist in areas ranging from clinical intervention to educational technology, and from brain–computer interfaces to artificial intelligence [751], with applications in developing new therapies for emotional rehabilitation programs, psychological trauma recovery, and other fields.

Furthermore, virtual experiments in cognitive psychology are made possible by simulation tools such as DeepMind's PsychLab [752], therefore allowing systematic testing of human-like learning and perceptual models. Concurrently, explainable AI studies, such as those by Taylor [753], integrate cognitive ideas to enhance interpretability, equality, and trust. These multidisciplinary projects taken together help to progress the creation of emotionally and socially conscious as well as functionally strong AI systems [754]. Moreover, AI is progressively supporting psychiatric science. From experimental modeling to behavioral diagnostics, AI helps to explore psychological dynamics and mental states using fresh approaches [755].

Beyond domain-specific applications, the psychological lens has also become essential for evaluating contemporary large-scale AI systems. The increasing powers of large language models (LLMs) like GPT-3 and GPT-4 caused serious concerns regarding the nature of machine intelligence and its interaction with human cognition. Shiffrin and Mitchell advocate a psychological assessment model for LLMs [756]. By use of cognitive vignettes like the Wason selection problem, they expose that LLMs reproduce human-like biases but lack clear reasoning capabilities. These results help to enable a change toward dynamic, interactive assessment systems that evaluate AI in line with human cognitive architecture.

Building on this perspective of psychologically anchored evaluation, Collins et al. recommend a human-in-the-loop assessment system called CheckMate, which uses conversational interactions across psychological domains, including trust and generosity, to evaluate LLMs [757]. Their findings highlight how views of AI efficacy are shaped by human expectations and interpretability. From the use of appraisal theories in modeling emotional trajectories [172] to the examination of human–model interaction dynamics in language model assessment [114], cognitive and affective processes are increasingly fundamental in creating responsive AI.

In parallel with empirical approaches, theoretical and mathematical models have sought deeper unifying principles for emotion and cognition within AI. Modern theoretical developments increase the psychological integration even more. Generative and Bayesian theories of emotional modeling are proposed by Tadić and Melnik [691] and Houlihan et al. [758]. Hartmann et al. [759] formalize emotional changes dependent on Scherer's appraisal theory using mathematical category theory:

$$\Psi(f_1, f_2, \ldots, f_n) \to [\text{APP}] \to \Lambda(\text{APP}_1, \text{APP}_2, \ldots, \text{APP}_m) \to [\text{Emotion}], \tag{32}$$

where Ψ maps raw features f_i to appraisal vectors [APP], and Λ aggregates assessments using a category framework to forecast emotions. This method allows graphic depictions of emotional dynamics, formal consistency checks, and transition modeling. Ambrosio, recently, provides a control-theoretic foundation for emotion-sensitive AI design by adding a wave-theoretic perspective on emotional development [100]. Taken together, these developments reveal a consistent trajectory across models, applications, and theories.

Ultimately, incorporating cognitive and affective psychology into AI marks a basic change toward emotionally intelligent, context-aware, and human-centric systems. Psychologically informed AI has the power to revolutionize how robots learn, interact, and cooperate with people, from aesthetics and music to social cognition and decision-making, therefore promoting more empathy, trust, and interpretability across technical ecosystems.

We have concluded Section 6 by highlighting how integrating psychological principles into advanced technologies, AI, and complex systems enhances human–computer interaction, adaptability, and decision-making under uncertainty. The insights presented here underscore the increasing requirement of human-centered design in technology developments where cognitive, emotional, and behavioral patterns are fundamental. Examining how comparable psychological bases show in financial and social contexts becomes essential given the interdependence of decision-making systems in both technological and socioeconomic spheres. Examining how cognitive biases, emotional influences, and social dynamics shape market behavior, policy responses, and institutional decision-making at both individual and collective levels, Section 7 thus turns the emphasis to finance, business, economics, and more general social sciences.

7. Psychological Effects in Finance, Business, Economics, and Other Areas of Social Sciences

Financial decisions are among the most important choices that people and institutions make. While traditional economic models assume rational individuals who maximize anticipated value, empirical evidence constantly shows that decisions are influenced by emotion, heuristics, and cognitive constraints. This part combines major contributions from behavioral finance and economic psychology, as well as mathematical formulations that reflect the effect of psychological states on economic dynamics, in line with the overarching goal of modeling biosocial and ecological systems.

- Cognitive and neural foundations of financial decisions: Frydman and Camerer examine how cognitive biases and brain processes influence financial behavior in a variety of areas, including household finance and business decision-making. They stress the role of overconfidence, overtrading, and insufficient financial literacy in driving unsatisfactory results. Neuroscientific research utilizing functional magnetic resonance imaging (fMRI) reinforces these behavioral trends by linking brain activity to risk perception and investment behavior [760].
  Frydman and Camerer [760], as well as Frydman et al. [761], use fMRI data to give empirical support for the "realization utility hypothesis", which holds that investors derive utility at the moment of realizing profits or losses rather than from intertemporal wealth growth. This behavioral inclination can be represented as follows:

$$U = \sum_{t=1}^{T} \delta^t \cdot u(R_t - P_t), \tag{33}$$

  where $\mathbf{R} = (R_1, R_2, \ldots, R_T)^T$ is the vector of realized returns over time, $\mathbf{P} = (P_1, P_2, \ldots, P_T)^T$ is the vector of corresponding purchase prices, and δ is a discount factor. The utility function u is determined not by total wealth but by the emotional enjoyment obtained from temporary gains or losses, particularly when selling assets. Taken together, these findings indicate that even at the most basic level of trading, emotional responses to realized gains and losses can systematically shape financial behavior.
  Kahneman and Tversky's prospect theory provides a psychologically based alternative to anticipated utility theory by elucidating how humans really assess risk and uncertainty. The conventional model posits a linear utility function with rational agents maximizing predicted utility. In contrast, prospect theory provides a value function defined by gains and losses relative to a reference point, rather than eventual wealth levels [762]. This function is concave for gains and convex for losses, which means that it becomes less sensitive as the amount of money lost increases. It is also

steeper for losses than for gains, which is in line with the idea of loss aversion, which says that losses are more important than gains of the same size. Mathematically, this is represented by a value function $v(x)$, which allocates a subjective value to each outcome x. In this case, x stands for the change in wealth compared to a reference point. Gains are positive and losses are negative. The function is defined as follows:

$$v(x) = \begin{cases} x^{\alpha}, & x \geq 0, \\ -\lambda(-x)^{\beta}, & x < 0, \end{cases} \tag{34}$$

where $\lambda > 1$ represents the degree of loss aversion, and $0 < \alpha, \beta < 1$ captures diminishing sensitivity to gains and losses [763]. Empirical estimates often indicate $\lambda = 2.25$, signifying that losses are often valued more than twice as much as corresponding benefits.

Prospect theory includes a probability weighting function in addition to the value function. This function reflects the fact that people tend to put too much weight on tiny probabilities and not enough weight on moderate to high probabilities. This conduct diverges from the utilization of objective probability in anticipated utility theory. The Prelec weighting function that is most often used is as follows:

$$\pi(p) = \frac{p^{\gamma}}{(p^{\gamma} + (1-p)^{\gamma})^{1/\gamma}}, \tag{35}$$

where $\gamma \in (0,1)$ shows how the distortion works. When $\gamma = 1$, the function becomes the identity line $\pi(p) = p$, which means that the perception is not skewed. For $\gamma < 1$, it has the S-shape that is typical of it, with low probabilities getting too much weight and high probabilities getting too little weight. Both the value function and the probability weighting function are the two main parts of prospect theory. They explain a lot of strange things that happen when people make decisions under risk, like the certainty effect, the isolation effect, and preference reversals. This makes prospect theory very important in behavioral finance and economics.

Frydman et al. provide additional evidence for the realized utility theory by demonstrating that brain responses, particularly in reward-related regions, correspond to the pleasure obtained from selling winning assets [761]. Recent emotional neuroscience research shows that brain signals from areas like the nucleus accumbens (NAcc) can predict market-level outcomes such as crowdfunding campaign success and collective investing decisions. These findings highlight how emotional and cognitive processes accessible by brain imaging help to better understand financial psychology and behavior [114].

Having established these micro-level cognitive and neural mechanisms, we can now examine how similar psychological forces scale up to shape aggregate market behavior and asset prices.

- Market behavior, investor biases, and overconfidence: Shiller questions the efficient market theory, demonstrating that stock values are too volatile due to investor mood, over-reaction, and herd behavior [764,765]. He considers market prices to deviate from fundamentals owing to investor mood. A basic mispricing dynamic, using sentiment $S(t)$, may be represented as follows:

$$\frac{dP}{dt} = \kappa(F - P) + \theta S(t), \tag{36}$$

where P signifies the observed price, F is the fundamental value, and θ weights the psychological sentiment. On the contrary, Odean and Barber show empirical

proof of the overconfidence bias and disposition impact, proving that these kinds of actions lower portfolio returns [766,767]. Barber and Odean highlight even more personal investor prejudices, including overconfidence-driven excessive trading and the inclination to sell successes while keeping losses [768]. Greenwood and Shleifer study extrapolative expectations, in which investors wildly extrapolate historical returns into the future, hence creating asset bubbles [769].

Beyond these market-wide anomalies, psychological limitations also manifest in how individuals construct portfolios and process basic financial information.

- Cognitive foundations and decision-making: Lusardi and Mitchell investigate the effects of inadequate financial literacy, stressing bad saving habits and credit mismanagement, often exacerbated by restricted attention and difficulties in grasping fundamental financial ideas such as compound interest [770]. Hedesström et al. and Benartzi and Thaler show that rather than addressing the mean-variance portfolio optimization issue, investors often depend on heuristics, including the naïve $1/n$ rule:

$$\max_{\mathbf{w}\in\mathbb{R}^n} \mathbf{w}^\top \boldsymbol{\mu} - \frac{\lambda}{2}\mathbf{w}^\top \boldsymbol{\Sigma}\mathbf{w}, \quad \text{subject to } \sum_{i=1}^{n} w_i = 1, \tag{37}$$

where n is the number of available assets, $\mathbf{w} = (w_1, w_2, \ldots, w_n)^T$ is the vector of portfolio weights, $\boldsymbol{\mu} \in \mathbb{R}^n$ is the vector of expected returns, $\boldsymbol{\Sigma} \in \mathbb{R}^n$ is the covariance matrix of returns, and $\lambda > 0$ denotes the investor's risk aversion. Heuristic-based decision-making of this kind sometimes results in ineffective diversification [771,772]. Unlike the efficient market hypothesis, which Shiller challenges with data of too much stock price volatility resulting from investor mood and herd behavior [764,765], other research implies that market efficiency may still be maintained. For example, Akdeniz et al. and Lewis and Whiteman find that under strong decision-making models and general equilibrium theories, efficiency could show up [773,774].

While these analyses focus on cross-sectional portfolio choice and market efficiency, psychological influences are equally pronounced in how people trade off consumption and saving over time.

- Financial literacy and temporal choice behavior: Detrimental financial conduct is mostly determined by low financial literacy. Lusardi and Mitchell demonstrate how poor knowledge of ideas like compound interest results in insufficient savings and credit misbehavior [770]. Benartzi and Thaler investigate the $1/n$ heuristic [772], in which investors forgo sophisticated research by simply diversifying blindly across choices. Hyperbolic discounting better captures time-inconsistent desires:

$$U = \sum_{t=1}^{T} \frac{u(c_t)}{1+kt}, \tag{38}$$

where U is the total utility, $u(c_t)$ is the instantaneous utility from consumption c_t at time t, and $k > 0$ reflects the degree of present bias. Berns et al. relate these kinds of behaviors to brain processes underpinning intertemporal decision, therefore relating impulsive expenditure to hyperbolic discounting [775]. Hershfield et al. show that seeing one's future self lowers current bias and promotes saving [776]. Thaler's theory of mental accounting helps one to understand how individuals divide their money, usually irrationally, which results in contradictory decisions in different situations [777].

Beyond cognitive limits and present-biased preferences, affective states and lived experiences further color how individuals perceive and manage financial risks.

- Emotional and experiential influences: Financial decision-making is much shaped by emotions and prior experiences, therefore questioning presumptions of logical conduct. Kuhnen and Knutson emphasize the neurological underpinnings of economic decisions by demonstrating how directly emotional emotions mediated by neurotransmitters such as dopamine impact risk preferences [778]. Cameron and Shah also discover that stressful events, including natural disasters, can cause ongoing changes in risk-taking behavior [779]. Following trauma, they model ongoing risk-aversion changes. One may write a dynamic utility formulation including emotional state $E(t)$ as follows:

$$U_t = u(c_t, \mathbf{E}(t)) \text{ with } \frac{d\mathbf{E}}{dt} = -\alpha \mathbf{E} + \beta \mathbf{X}_t, \tag{39}$$

  where X_t captures traumatic or emotionally salient events, and α is the decay rate of emotional impact. This highlights emotion–memory coupling in behavioral responses. Personal financial history is also very important. Malmendier and Nagel show that those who experienced significant inflation during formative years often choose more cautious investing approaches [780]. Hoelzl and Huber highlight the limits of experience foresight in financial planning, as borrowers can understate long-term repayment obligations, which results in over-indebtedness [781]. Beyond financial situations, subjective emotional states have great predictive power. Simple self-reported emotions, according to Kaiser and Oswald, can predict behavior like job changes and hospital visits better than conventional economic indicators [782]. Under uncertainty and adaptive dynamics specifically, these results highlight the need to include emotional and sensory aspects in models of economic and social behavior. Roberts et al.'s affect-informed decision paradigm also provides insightful analysis for economic psychology, as it shows that emotional valence may change perceived value under various contextual weightings, thereby changing economic choice behavior [151]. These findings naturally connect to broader economic–psychological frameworks that formalize how subjective states mediate between objective environments and observable economic behavior.
- Economic psychology and mental models: Economic psychology focuses on the connection between mental processes and economic behavior. Examining how motivation, perspective, decision-making, and social factors impact financial decisions, Antonides offers an integrated picture of psychology and economics [783]. Based on psychological motives and resources, the book explores the Values and Lifestyles (VALS) model, which puts readers into categories including Survivors, Achievers, and Emulators. Structured as a causal chain, Figure 2 offers a fundamental economic psychology model: the external environment (e.g., money; employment) impacts mental processes (e.g., attitudes; expectations), which in turn define behavior (e.g., spending; saving). Rooted in behaviorist psychology, this S-O-R (Stimulus–Organism–Response) model shows how subjective interpretation moderates the effect of economic stimuli [784–786].



Figure 2. A basic economic psychological paradigm.

By separating objective economic elements from subjective psychological processes, Figure 3 broadens this model and shows how mental representations, emotions, and societal standards shape financial conduct. This framework shows how closely economic conduct is ingrained in a larger framework of social influence, perspective, and motivation [783].

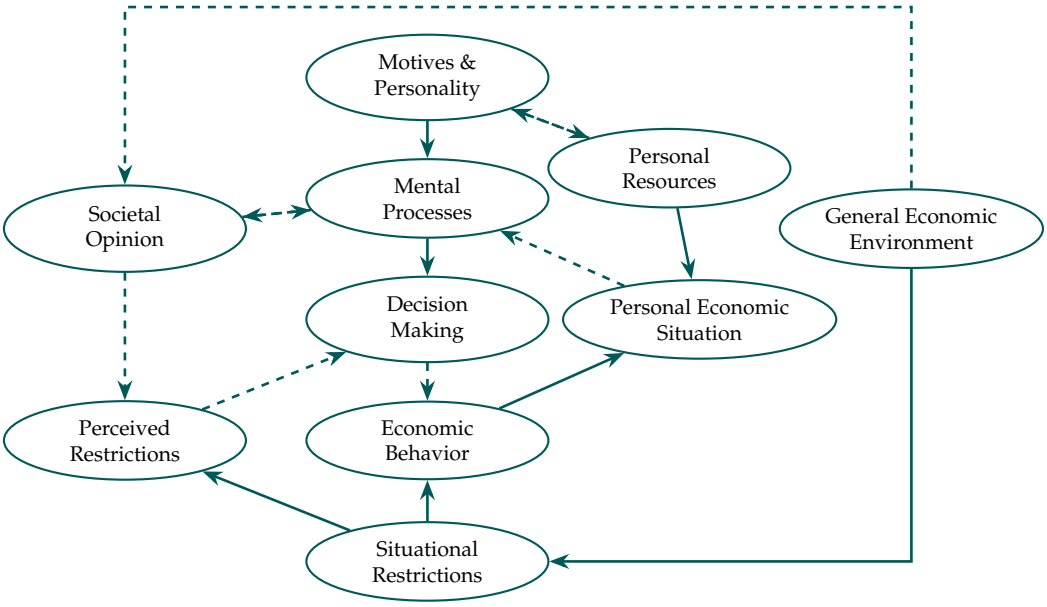


Figure 3. The structural foundation of economic behavior is built on both objective and subjective factors.

At the level of strategic interaction, these psychological foundations become especially salient when individual incentives conflict with collective welfare.

- Strategic behavior and collective outcomes: The Prisoner's Dilemma is a prime example of how individual rationality could produce collectively less than ideal results in economic settings. Using this approach, Antonides emphasizes the need for trust, justice, and social conventions in allowing collaboration and enhancing results beyond what simple self-interest suggests for financial decisions [783].
  Relatedly, when economic behavior is embedded in institutions such as taxation and public spending, psychological responses to fairness and norms can strongly influence contributions to public goods.
- Crowding-out effect and public goods: Economic psychology, to a great extent, investigates how psychological incentives influence public policy responses. It clarifies voluntary contribution decreases under taxes by means of the following equation:

$$G_i = \theta_i - \phi(T) + \psi(S), \tag{40}$$

where G_i signifies the individual contribution, θ_i is intrinsic motivation, $\phi(T)$ denotes the perceived fairness loss due to taxation, and $\psi(S)$ represents the effect of social norms. The crowding-out effect explains how higher government expenditure could lower public good voluntary donations. Apart from substitution effects, this phenomenon is driven by perceived justice, societal conventions, and personal beliefs that defy the conventional wisdom of only maximizing behavior [783].
Psychological determinants of economic behavior are equally crucial when individuals and societies confront risks that are complex, low-probability, or difficult to interpret.

- Risk perception and societal decision-making: Slovic and associates investigate how people discern danger, depending more on emotions and heuristics than on probability [787–793]. These impressions help to form reactions to public hazards, financial risks, and legal rules. Slovic contends, in reality, that emotional heuristics define risk, and the expected value becomes [789]:

$$U = \int p(x) \cdot u(x, A(x))dx, \tag{41}$$

where $A(x)$ is the affective response associated with the outcome x, often diverging from statistical risk assessments. Garling et al. contend that financial crises are caused in part by psychological elements like capital delusion, framing effects, and crowd behavior. They support better financial education that seeks to reduce such prejudices [794].

These insights have direct consequences for how markets are regulated and how policies are designed to protect consumers and maintain stability.

- Policy implications and regulation: Campbell et al. investigate how present and status quo bias among behavioral biases affect consumer saving and investment, therefore implying the requirement of customized treatments [795]. According to Akerlof and Shiller, sometimes systemic crises result from emotions, tales, and group dynamics over-riding logical conduct in financial markets [796]. Models of debt and savings guided by behavior combine limited rationality and status quo bias. For example, Bertrand et al. demonstrate that psychological frictions like complexity and framing affect consumer choices on credit intake in addition to interest rates [797]. These results draw attention to cognitive overload and status quo bias, which may be abstracted as a threshold-based behavioral paradigm whereby changes only occur if perceived value increases surpass a psychological cost. Mathematically, it can be modeled as follows:

$$d = \begin{cases} 1, & \text{if } U_{\text{alter}} - U_{\text{status}} > \Delta, \\ 0, & \text{otherwise,} \end{cases} \tag{42}$$

where Δ is a threshold for inertia reflecting emotional or cognitive conflict, and status quo bias suggests that change is avoided until advantages exceed Δ. Also, $U_{\text{alter}} - U_{\text{status}}$ denotes the net utility gain from switching from the current (status quo) to a new state, and $d \in \{0, 1\}$ signifies the decision to accept $(d = 1)$ or reject $(d = 0)$ a credit offer. Bertrand et al. look at cognitive overload and framing in debt decisions; Lewis addresses psychological aspects of tax compliance [798]. Selective attention biases shown by Sicherman et al. help to explain overtrading and inadequate asset allocation [799].

Debates over market volatility and efficiency further illustrate how far psychological considerations have reshaped the interpretation of financial dynamics.

- Alternative views on market volatility: Shill stresses elevated volatility in stock prices [764]; however, Akdeniz et al. and Lewis & Whiteman provide counterpoints demonstrating that markets may stay efficient or even under-respond to information when modeled under general equilibrium or strong decision frameworks [773,774].

This review shows the need for including psychological insights into financial and economic models. Behavioral finance offers a more realistic framework for analyzing policy design, market behavior, and decision-making by including cognitive limits, emotions, and biases.

At the broadest level, these strands of research converge in explaining how psychological forces contribute to financial instability and large-scale economic crises.

- Broader implications and financial crises: Cognitive biases, including overconfidence, framing effects, and herd behavior, help to explain financial instability and crises, according to Garling et al. and Akerlof and Shiller [794,796]. Lewis and Bertrand et al. stress how behavioral biases also influence tax compliance and debt behavior [797,798]. Slovic's research on risk perception emphasizes how different people misinterpret financial dangers depending on emotions and heuristics, therefore deviating from professional opinions [788,789,791].

The literature shows that a complicated interaction of cognitive biases, emotional reactions, social influences, and environmental elements shapes financial decision-making. More realistic and predictive tools are provided by models including psychological variables, such as the S-O-R paradigm and economic–psychological models, than by standard rational-agent theories. For policy planning, financial education, and market control, this multidisciplinary approach offers essential new perspectives.

From individual cognition and behavior to ecological interactions, epidemic dynamics, and socio-economic systems, Sections 2–7 illustrate how cognitive traits, emotional responses, and behavioral biases shape outcomes at both personal and systemic levels. Given this wide-ranging influence, it becomes essential to examine how these psychological components interact within decision-making, the core mechanism driving behavior across these environments. Section 8 thus explores how cognitive biases, emotions, memory, and perception affect decisions made by people and groups in uncertain and complex contexts, thereby focusing on decision-making under the effect of psychological variables.

8. Decision-Making with Psychological Effects

Defined as the use of insights gained from organized and unstructured data to direct activities, data-driven decision-making has become fundamental in modern decision architectures [800]. This paradigm emphasizes the premise that decision quality usually determines success or failure and affects not just institutional policies but also personal decisions [801,802]. From data mining to machine learning to AI, data serves as a basic input across many fields, identifying latent trends and producing useful insights [803]. With increasing relevance during the COVID-19 epidemic, its importance has especially been highlighted in fields including business, education, and healthcare [804–809]. Thus, especially in educational and policy environments, inclusive and context-sensitive decision-making depends on promoting fair access to data and data literacy [810].

Data analytics and machine learning helped epidemic forecasting [811], contact tracking [812], hospital resource allocation [813], economic planning [814,815], psychological assistance [816,817], and policy optimization [818–822] throughout the pandemic. These initiatives, however, show that data by itself is inadequate; cognitive and emotional processes essentially affect how people understand and behave with knowledge. This shift from raw information to human interpretation highlights the need to examine how perception and cognition shape data-driven decision-making.

8.1. Visual Cognition and Cognitive Biases

When well-designed, visualizations become essential interfaces between data and human judgment, improving accuracy, confidence, and efficiency [823–825]. But cognitive biases like salience, anchoring, and framing can skew interpretation [826–832]. User experience, cognitive load, and job complexity reduce their impact [833]; even highly graph-literate people are prone to misjudging under ambiguity [824].

Although complex images, such as violin diagrams, help with statistical knowledge, their unfamiliarity runs the risk of confusing things [834]. Although interactive dashboards save cognitive effort, designs that are too complicated may cause new interpretative mistakes [835]. Visualizations' perceptual influence may be modeled as follows:

$$u(t) = B(\mathbf{V}(d_t)), \tag{43}$$

where $\mathbf{V}(d_t)$ represents the visual encoding of data d_t, and $B(\mathbf{V})$ denotes perceptual bias. Accounting for cognitive load yields the following:

$$\tilde{u}(t) = B(\mathbf{V}(d_t)) - \psi(\mathbf{V}), \tag{44}$$

where $\psi(\mathbf{V})$ assesses mental effort under time constraints or low familiarity.

In high-stakes industries like law enforcement and banking, judgments in visual aspects, including color, layout, and salience, greatly affect choices [836–841]. Though deceptive, consumers typically trust visual information more than written material [842], and subtle emotional signals in images can unconsciously impact user behavior [843].

8.2. Emotion, Sleep Deprivation, and Risk-Taking

Beyond perceptual biases, internal physiological and emotional states further distort how individuals assess risk and make choices. Studies of neurocognitive processes show that sleep deprivation and emotional states impair executive control and raise risk-taking [844–849]. Lim et al. discovered that under loss framing, sleep-starved men become more risk-seeking, whereas under gain framing, women become more risk-averse [850]. Neuroimaging studies demonstrate that sleep loss reduces prefrontal connection, hence altering inhibition and risk assessment [851–853]. Recent developments in affective science have also codified the way people choose among emotional regulating techniques in response to different emotional intensities. Using a computer model, Petter et al. explained why people often choose reappraisal during lower-intensity emotional states and distraction during high-intensity ones [854]. By converting verbal theories of control strategy choice into formal mathematical language, their work reveals hitherto unnoticed assumptions and generates testable hypotheses regarding the adaptability of strategy usage throughout several circumstances. Such models not only improve our knowledge of emotional regulation but also provide a good basis for psychiatric treatments and decision-support systems. These mechanisms of emotional regulation naturally connect to broader patterns of impulsivity and affect-driven errors in judgment.

These results cross with studies on emotion-related impulsivity (ERI), defined as the inclination to behave impulsively in elevated emotional states [855]. This behavioral tendency aligns with the realization utility framework introduced in Equation (33), which models utility as being derived from momentary gains or losses rather than long-term wealth accumulation [761]. In this context, the vectors $\mathbf{R} = (R_1, R_2, \ldots, R_T)^T$ and $\mathbf{P} = (P_1, P_2, \ldots, P_T)^T$ again denote realized returns and corresponding purchase prices over time, and δ represents the discount factor. Emotion modulates the curvature of $u(\cdot)$, hence improving sensitivity to losses or gains. ERI is linked to underperformance in tasks including the Iowa Gambling Task and Delay Discounting [856–860]. Further revealing increased insula-prefrontal activity during risk-taking in high-ERI persons, neural findings point to a breakdown in cognitive control under emotional pressure [861–865]. This study supports the theory that people with high ERI are especially prone to affect-driven choice errors in uncertain or high-stakes environments. Using dynamic frameworks that combine emotional states with decision-making processes, recent computer models have codified such emotion-driven departures from rationality. To recreate erroneous behaviors, including emotionally motivated criminal activities, Iinuma and Kogiso [866] created an emotion-oriented decision model integrating a partly observable Markov decision process (POMDP) with nonlinear emotional dynamics. Under different levels of stress, affect, and memory, their model shows how dynamic emotional states control the chance of choosing logical rather than illogical behavior.

A similar set of emotional and cognitive distortions also appears in financial contexts, where high stakes amplify the impact of biases. Financial judgments are much shaped by cognitive biases, which also methodically affect investor behavior. Especially in Asian markets, Shah et al. stress important biases like overconfidence, anchoring, herding, and loss aversion [867,868]. While emotionally charged events like earnings announcements frequently drive irrational trading [869], heuristic-driven biases like representativeness and

availability also skew views of market dynamics [870]. According to Ifcher and Zarghamee, perceived responsibility increases decision-making for others (DMfO), hence changing risk choices [871]. In corporate finance, particularly in high-volatile sectors like environmental remediation, data-informed heuristics increasingly direct decision-making [872,873].

Such decision distortions extend well beyond investment settings, manifesting just as prominently in consumer and marketing environments where psychological mechanisms directly influence data-driven practices. Similar cognitive and emotional processes also find expression in consumer marketplaces, where psychological insights change data-driven marketing plans progressively. Psychological profiling is closely associated with predictive modeling, AI, and big data analytics in modern marketing and consumer behavior [874–878]. Empirical research supports a favorable correlation between businesses' marketing analytics skills and their performance results [879–883].

Moreover, the acceptance of explainable AI in marketing systems has improved interpretability and transparency, thereby building more customer confidence in automated judgments [876]. On the other hand, the employment of deceptive or badly crafted visuals could backfire and discourage consumer information-seeking as well as inspire impulsive or less-than-ideal decisions [884–886].

To generalize these observations, state-dependent utility models formalize how emotional fluctuations directly enter decision processes. In situations encompassing threat and emotional stimulation, these psychological factors especially matter. A state-dependent utility framework can help a person capture consumer risk preference under physiological or emotional stress, such as sleep deprivation or emotional impulsiveness (ERI):

$$U = \mathbb{E}\left[\sum_{t=0}^{T} \delta^t \cdot u(\mathbf{x}_t, r(t))\right], \tag{45}$$

where $\mathbf{x}_t$ denotes the consumption or decision outcome at time t, $\delta \in (0,1)$ is the intertemporal discount factor, and $r(t)$ reflects time-varying risk sensitivity modulated by affective states [853,855]. This formulation shows how moment-to-moment emotional changes can skew perceived utility, hence influencing consumption habits or biased market reactions.

8.3. Stochastic Dynamics Under Uncertainty

Building on emotion-modulated utility, stochastic frameworks provide a natural way to model decisions made under uncertainty and noise. Stochastic differential equations (SDEs) let one simulate decision-making under uncertainty:

$$d\mathbf{x}(t) = \mathbf{f}(\mathbf{x}(t), \mathbf{u}(t), \boldsymbol{\theta})dt + \boldsymbol{\sigma}(\mathbf{x}(t))dW_t, \tag{46}$$

where $\boldsymbol{\sigma}(\mathbf{x}(t))$ captures decision noise, and W_t is a Wiener process reflecting random perturbations [887]. This paradigm fits reactions to epidemics, environmental initiatives, and financial decisions. Modeling decisions in ecological systems, investment behavior, or epidemic reactions calls specifically for this paradigm. Furthermore, stochastic modeling provides a solid grounding for describing decision-making under uncertainty. These ideas have been used in fields including military strategy [888,889], finance [890], transportation [891], and logistics [892]. Celik et al. reviewed stochastic choice methods, including dominance analysis, prospect theory, and regret theory, that include cognitive uncertainty and behavioral variability [887]. Using a spin-based agent model, the work of Sevinchan et al. examined how network structure, social influence, and bias control group decision-making [893]. The authors computed the system's sensitivity to perturbations and demonstrated that maximum decision responsiveness develops near critical points. This affects the adaptive decision-making in biosocial systems under noise and ambiguity.

These models not only help to maximize choices but also recognize human irrationalities and perceptual distortions.

8.4. Psychological Feedback in AI Systems

As decision environments increasingly incorporate AI systems, human psychological responses to automation also become central to decision outcomes. Recent research has shown that large language models (LLMs) imitate human biases. Outputs vary depending on framing, token order, and uncertainty [756]. In human–AI interaction, decision utility may be described as follows:

$$U_{AI} = \boldsymbol{\omega}^{\top}\mathbf{X} = \alpha \cdot A_{ex} + \beta \cdot T + \gamma \cdot R, \tag{47}$$

where $\mathbf{X} = (A_{ex}, T, R)^T$ is a vector of AI system features such as accuracy, transparency, and explanation, and $\boldsymbol{\omega} = (\alpha, \beta, \gamma)^T$ is the corresponding vector of user preference weights [757]. Users prefer interpretable, psychologically aligned systems over completely accurate but opaque models.

Beyond faith in AI accuracy and explanation, larger psychological views of justice, moral detachment, and domain sensitivity influence user adoption and resistance. AI has increased the complexity of decision-making psychology. It affects people's sense of fairness and trust in decision-making [894,895]. While automation promises impartiality, many users believe that completely automated judgments are ethically distant or demeaning [896–898]. In contrast, AI–human hybrid systems are more widely accepted. The impartiality of AI is assessed differently depending on the domain—decisions in objective domains, such as admissions, are more acceptable than those requiring moral or personalized judgments [899,900]. In the workplace, algorithmic hiring diminishes perceived human warmth and may discourage applicants [901]. Gig economy workers have resisted algorithmic control by forming online communities and exchanging knowledge [902,903]. These dynamics emphasize the need for AI systems that are open, responsible, and matched with users' psychological expectations, particularly in sensitive domains like healthcare [904,905].

8.5. Dynamic Decision Systems and Trait Modulation

Decision-making is not static; internal cognitive and emotional states evolve over time, shaping how new information is processed. Internal decision states transition throughout time in response to facts and human characteristics. This may be represented as follows:

$$\frac{d\mathbf{x}(t)}{dt} = \mathbf{f}(\mathbf{x}(t), \mathbf{u}(t), \boldsymbol{\theta}), \tag{48}$$

where $\mathbf{x}(t)$ denotes the cognitive or emotional state, $\mathbf{u}(t)$ represents the external stimulus, and $\boldsymbol{\theta}$ includes traits like risk aversion or memory decay. According to appraisal theory, perceived control and responsibility impact motivational dynamics, resulting in either approach or avoidance tendencies [691]. Valletta et al. investigated how machine learning has improved the modeling of complex behavioral patterns in animals, particularly in social dynamics, locomotion, and emotion-related behaviors. They provide technologies that blend animal psychology with ecological decision systems [906].

8.6. Collective Decision-Making and Emergent Responsiveness

These individual-level processes scale up in social settings, where group structure and interaction patterns give rise to collective decision phenomena. Collective decision-making is critical for structuring collective responses to complex and unpredictable contexts. Recent research has highlighted its importance in systems where agents interact under uncertainty

and social influence. Sevinchan et al. created a spin-based agent model with diverse biases and adjustable network topologies, revealing that collective responsiveness peaks at important areas of susceptibility [893]. This state, defined by increased sensitivity to external disturbances, enables groups to respond quickly to changing situations. Biological environments, such as predator–prey interactions, exhibit comparable processes. Klamser and Romanczuk demonstrated that prey schools operate best near criticality, not because of greater individual decision-making, but because of emergent spatial structure that increases evasion success [444]. Bartashevich et al. have also shown how animals under assault conduct coordinated escape movements, such as the 'fountain effect', resulting from basic social heuristics and predator-specific attack techniques [414]. Furthermore, Pacher et al. discovered that in group hunting settings, mobile prey schools display patterns of isolation and capture that promote predator cooperation, indicating a type of by-product mutualism [370]. Thieu and Melnik extended these principles to human systems, proposing a complete framework for social human decision-making in the face of ambiguity [93]. Their model explains behavioral phenomena, including escape route selection, crowd cooperation, and neuromodulated learning, by combining probabilistic drift-diffusion processes and Bayesian inference with brain network dynamics. Recent multidisciplinary insights underscore the necessity of comprehending cooperation as a dynamic, contextually responsive process. In [907], authors from neuroscience, sociology, and systems theory emphasize that cooperation does not possess a universal structure and is significantly shaped by multi-scale processes and cultural border conditions. This corresponds with developing theories in biosocial systems, wherein collective outcomes depend on adaptive coordinating processes influenced by emotion, cognition, and circumstance. These multidisciplinary methods support the concept that decision-making is an emergent trait of socially and ecologically integrated systems, rather than the result of separate cognitions.

8.7. Applications to Biosocial and Ecological Systems

The same psychological and collective mechanisms play crucial roles in biosocial systems, especially where emotions, risk perception, and social influence drive public health behaviors. Emotional contagion, framing, and institutional trust all influence decision-making in biosocial systems, including immunization, conservation, and policy compliance. Wu and Huo's latest model formalizes these dynamics using a UAU-WVW-SIS tri-layer multiplex network, which integrates information dissemination, vaccination behavior, and disease transmission with changing emotional states [908]. Their concept describes how emotional states, such as anxiety or stability, impact a person's propensity to seek information, engage in preventive activities, and adapt to local disease incidence. The model incorporates emotional thresholds driven by global information and local infection pressure, illustrating how emotional contagion and informational exposure interact to modify epidemic trajectories. Stochastic models that incorporate psychological realism, cognitive biases, and emotional states have higher prediction power and policy implications [887]. Sevinchan et al.'s findings shed more light on how ecological networks (for example, animal collectives) may modify their structural susceptibility to remain near criticality, aiding adaptive group decisions and paralleling natural escape behavior and predator avoidance methods [893]. These methods emphasize the need to account for psychological variation and emotional feedback when developing successful biosocial treatments.

Decision-making nowadays is not only a computer process but also essentially psychological, shaped by emotion, intellect, bias, and situation. From data visualization to sleep deprivation, from AI cooperation to investment behavior, psychological elements are fundamental in determining the quality, openness, and efficacy of decisions in biosocial and ecological systems.

Building on the investigation of decision-making impacted by psychological aspects in Section 8, it is clear that human behavior, particularly in dynamic, unpredictable contexts, often deviates from equilibrium-based models and linear assumptions. The feedback loops, delayed reactions, memory effects, and nonlocal interactions that define real-world psychological and behavioral dynamics challenge conventional models. The following part explores nonequilibrium events, nonlocality, and complicated psychological behavior in order to handle these complexities and offers a theoretical and mathematical framework able to capture the subtleties seen in human cognition and decision processes across many systems.

9. Nonequilibrium Phenomena, Nonlocality, and Complex Psychological Behavior

Life is inherently a nonequilibrium process. Biological and cognitive systems operate far from thermodynamic equilibrium, constantly exchanging matter, energy, and information across various spatial and temporal scales. The brain exemplifies a nonequilibrium system, characterized by enduring activity that signifies irreversible dynamics, historical dependency, extensive correlations, and continual adaptability. In decision-making and emotional regulation, these dynamics produce temporally asymmetric and path-dependent processes. Ashby's seminal research on self-organizing systems formulated a systems-theoretic framework for emergent complexity in open, dissipative systems [909], thus establishing a foundation for synergetics and nonlinear modeling in biological and cognitive fields.

A common thread among physical, biological, and psychological systems is that memory, nonlocality, and chaotic transients function as structural mechanisms in nonequilibrium behavior. Numerous studies from several disciplines illustrate the emergence of similar characteristics across different dimensions. Lazarević utilized synergetic principles and fractional calculus to formulate a mathematical phenomenology of self-organization, highlighting the influence of memory kernels and nonlocal operators on emergent dynamics [910]. Building on this viewpoint, Rylands and Andrei examined nonequilibrium quench dynamics in integrable many-body systems, including the Lieb–Liniger gas and Heisenberg spin chains. Their findings indicate that conserved quantities and long-range correlations obstruct complete thermalization, facilitating the dynamic retention of knowledge regarding the starting state—essentially a manifestation of physical memory [911]. Although originating in a quantum framework, this mechanism serves as a conceptual parallel for history-dependent processes in biological and cognitive dynamics. Pal and Melnik's fractional-order network model of Alzheimer's disease illustrates how non-Markovian memory influences neurodegeneration via nonlocal connectome-level coupling [912]. Collectively, these studies demonstrate that memory-preserving nonequilibrium processes are not confined to specific domains but embody general dynamical principles.

Thermodynamic frameworks have been adapted to work in conditions that are not in equilibrium. Cimmelli et al. suggested a weakly nonlocal formalism for heat transmission far from equilibrium, motivated by second sound and anomalous heat transport [913]. In a complementary manner, Maes redefined fluctuation–dissipation relations to include memory, demonstrating how nonequilibrium limitations alter traditional thermodynamic predictions [914]. In the field of psychology, Ambrosio characterized emotional processes as wave-like states that interact with each other and are controlled by feedback from social and cognitive sources that are not local [100]. Thieu and Melnik also constructed a hierarchy of nonequilibrium and nonlocal models to explain how people operate in complicated situations like emergency response, combining fractional dynamics, biosocial feedback,

and temporal memory [915]. These advancements illustrate the inherent applicability of nonequilibrium formalisms to psychological and ecological decision-making.

Sengupta posited that self-organization, chaos, and feedback represent a generalized form of nonlocal entanglement across several scales [916]. Poznanski's Dynamic Organicity Theory similarly ascribes awareness to multi-scale thermodynamic and quantum–thermal interactions governed by negentropic fluxes [917]. Sanz Perl et al. empirically demonstrated that nonequilibrium indicators, including entropy production and rotating probability currents, distinguish between conscious and unconscious states [918]. Tschacher and Haken's synergetic viewpoint posits that cognitive functions—intentionality, time-consciousness, and meaning-making—emerge from nonequilibrium self-organization [919,920]. Freeman also stressed the role of chaotic neural processes in purposeful behavior and spontaneous symmetry breakdown [921]. In practical settings, Eisbach et al. demonstrated that machine learning models that combine psychological theory with explainable AI display emergent nonequilibrium behavior pertinent to motivation and team dynamics [922].

Nonlocality, which started out as a part of quantum theory, is now becoming more and more important in biological and psychological systems. Pribram's holonomic brain theory posits that memory and consciousness arise from dispersed interference patterns, suggesting nonlocal information encoding [923]. Hameroff and Penrose's Orch OR framework posits that quantum coherence in brain microtubules, maintained by nonequilibrium mechanisms, plays a role in consciousness [924]. Sargsyan and Karamyan's empirical research demonstrated quantum-like nonlocal interactions between mental and physiological states [925]. These concepts correspond with neuron–glial simulations conducted by Pal and Melnik, illustrating how nonlocal coupling, astrocytic memory, and stochasticity facilitate neurodegeneration progression [926]. Their fractional-order network model encapsulates psychological feedback mechanisms, including anticipation, fear, and risk perception.

Memory is also important in psychology and nonequilibrium physics. Lutz, Burov, and others showed that fractional Langevin equations with memory lead to strange transport and power-law diffusion [927,928]. Silva et al. constructed Fokker–Planck equations from recursive memory-driven random walks, emphasizing historical dependency in emerging processes [929]. Reeves et al. demonstrated that memory terms often overlooked in GKBA approximations are crucial for precise long-term evolution in quantum many-body systems [930]. Balzer et al. corroborated analogous memory needs in ultrafast Hubbard-cluster dynamics [931].

Psychological models display analogous structures. Carbonaro and Serra [121] formulated a kinetic model of emotional transitions using integro-differential equations:

$$\frac{\partial}{\partial t}\boldsymbol{\pi}_A(x,t) + \frac{\partial}{\partial x_A}(\boldsymbol{c}_A(x,t)\boldsymbol{\pi}_A(x,t)) = \boldsymbol{J}_A^{(e)}(\boldsymbol{\pi}_A, \boldsymbol{\pi}_B), \tag{49}$$

where

t: time;

x_A: real-valued state variable representing the emotional intensity (e.g., affection or rejection);

$\boldsymbol{\pi}_A(x,t)$: probability density function (PDF) of individual A's emotional state x at time t;

$\boldsymbol{c}_A(x,t)$: time-dependent inner evolution rate (velocity) of the emotional state x for individual A;

$\partial(\boldsymbol{c}_A\boldsymbol{\pi}_A)/\partial x$: transport term capturing propagation of internal changes in emotional space;

$\boldsymbol{J}_A^{(e)}(\boldsymbol{\pi}_A, \boldsymbol{\pi}_B)$: external interaction term (gain-loss type) that models the stochastic effect of interactions between individuals A and B, which includes probabilistic changes in feelings due to actual encounters or communication, and depends on both individuals' emotional state distributions $\boldsymbol{\pi}_A$ and $\boldsymbol{\pi}_B$.

This formulation naturally incorporates feedback, emotional memory, and nonequilibrium adaptation.

Stochastic and disease-related systems provide additional examples of these principles. Pal et al. simulated stochastic instability in Alzheimer's cognitive pathways [932], noise-induced effects in ecological predator–prey dynamics [933], and memory-modulated emotional processing through nonlocal neural interactions [20]. Quantum-inspired psychological models illustrate emotional contagion and interpersonal resonance via nonlocal correlations [934–936]. Wang et al. demonstrated that long-term memory in nonequilibrium diffusion influences information flow within social opinion dynamics [937]. Messori's thermodynamic phase-transition model conceptualizes cognition as a resonant attractor landscape influenced by energy flows [938], aligning with the 5E cognition structure (embodied, embedded, enactive, extended, and emotive) [939].

Machine learning further substantiates this correlation. For example, Seif et al. proved that models trained on stochastic processes may deduce thermodynamic time-directionality and irreversibility, reflecting the dissipative character of psychological trajectories [940]. Tadić et al. revealed that emotional interactions on social networks have self-organized criticality in digital contexts, with 'emotional avalanches' happening inside behavioral cycles [9]. These results encourage the use of dynamic and agent-based modeling techniques to address psychological complexity.

Wood and Coan contended that in person–environment systems, emotions operate as emergent attractor states influenced by feedback and environmental affordances, rather than as static biological modules [941]. This is quite similar to nonequilibrium ideas like degeneracy, amplification, and attractor flipping. Scherer and Moors' process-oriented model of emotions gives more structure by explaining how emotional responses happen over time through repeated evaluations of uncertainty [4]. This demonstrates the multiscale nonequilibrium characteristics of psychological behavior.

Taken together, these investigations demonstrate that memory effects, nonlocality, and nonequilibrium dynamics are foundational principles across physical, biological, and psychological systems, offering a unified framework in which long-range interactions, history dependence, and intrinsic instability give rise to emergent cognition, emotion, and consciousness.

10. Conclusions and Future Directions

Including aspects specific to emotions into biosocial and ecological systems provides a fresh viewpoint on the dynamics in these intricate systems. Knowing how emotional reactions affect both personal and collective activities helps one create models that better depict the interactions forming biological communities. Moreover, knowledge of how emotional reactions affect individual and group activities might help to create models that more faithfully depict ecological community interactions. Traditionally based on population dynamics, predator–prey models, for instance, acquire more layers of accuracy when psychological elements, such as fear or stress, are included, thereby representing the multifarious character of these interactions. This approach recognizes that reactions that influence mobility, danger assessment, and resource competition, among other elements, shape behavior in addition to survival instincts.

The scope and intricacy of psychological impacts in humans are different from those seen in predator–prey relationships. In humans, feelings like stress, empathy, and terror influence social norms and collective actions in addition to influencing individual choices. In contrast, psychological impacts in predator–prey models are frequently confined and instantaneous, resulting from fear reactions that change aggressive or avoidance behaviors in particular contexts. The significance of simulating human psychological consequences

in a manner that encompasses both individual cognition and its impact on social systems is underscored by these distinctions.

The psychological effects on human and predator–prey dynamics vary greatly as conscious awareness and cognition play such important roles in humans. Human psychological reactions result in social systems with complicated feedback loops wherein emotions influence decisions, therefore influencing emotions within groups or civilizations. By contrast, predator–prey psychological dynamics mostly influence individual survival and immediate ecological interactions without any input into social norms or long-term societal changes. This difference emphasizes the requirement of several models when using psychological insights in many spheres to guarantee correct and relevant applications.

Psychological consequences on brain networks also affect biosocial dynamics, as neural reactions to emotional components can direct group-level as well as individual behaviors. Knowing these brain–behavior linkages helps one to better understand how people react to stress or anxiety and how these reactions taken together fit a group or species. In biosocial settings, where emotional processing greatly influences social interactions and decision-making and can therefore impact more general systems, this understanding is invaluable. Investigating these psychological processes at the brain level might potentially expose fresh links between social and biological reactions, supporting general system vulnerability or stability.

This review will help to synthesize present knowledge on emotion-specific elements in ecological and biosocial systems as well as foster new, more precise modeling prototypes. It described current models, pointed out areas of weakness, and suggested modeling-based multidisciplinary methods using psychological insights. While investigating the neurological bases of emotional behavior in humans as well as animals, future studies should concentrate on building models that combine these discoveries across numerous domains, from individual neurons to social influences. In the long term, developing this discipline might increase the prediction ability of social and environmental models, thereby enhancing the methods for ecological management and knowledge of human socio-ecological interactions.

Integrating emotion-specific elements, notably fear and anxiety, into predator–prey models has greatly improved our knowledge of ecological dynamics and their wider implications for biological and social systems. This technique has shown that predators' non-consumptive effects (NCEs) on prey populations can be just as powerful as direct predation, impacting behavior, physiology, and even evolutionary paths. The integration of psychological impacts into these models has bridged the gap between ecology, neuroscience, and psychology, providing a more comprehensive understanding of how fear changes ecosystems and individual species.

First of all, the research on predator-induced fear in animals has already provided an important new understanding of human psychology, especially in relation to anxiety disorders and post-traumatic stress disorder (PTSD). Studies of the neurological processes behind fear reactions in prey animals have shown unexpected similarities between them and those seen in people after trauma or chronic stress [942]. This similarity has opened fresh paths for studying and treating PTSD and other anxiety-related illnesses in humans by use of animal models for these diseases [942,943].

At the modeling level, nevertheless, it is important to acknowledge the differences between psychological effects in predator–prey models and human psychological effects. Although both entail terror reactions, the setting and intricacy are very different. Mostly motivated by urgent survival demands, animal reactions have been molded over millennia by evolutionary forces. On the contrary, human psychological reactions are shaped by a complex interaction of social, cultural, and personal elements spanning beyond instan-

taneous physical hazards [944]. Higher cognitive skills among humans enable abstract reasoning about fear and stress, therefore enabling possibly more complicated and long-lasting psychological impacts.

Brain networks and biosocial dynamics are profoundly affected by the psychological consequences witnessed in predator–prey encounters. Research on exposure to predator cues has shown that, especially in areas connected to fear processing, like the amygdala and hippocampus [942], exposure can result in long-lasting alterations in brain structure and function. Long-term behavioral changes like increased alertness and changed social interactions might follow from these neurobiological changes [945]. Moreover, by means of changes in reproductive behavior, feeding habits, and habitat usage, predator-induced fear can affect population dynamics and ecosystem functioning outside of individual animals [261]. Studies in the future should mostly focus on a better knowledge of the interactions across brain networks, their structures, and biosocial dynamics, including psychological impacts.

From a quantitative standpoint, subsequent research can be strengthened by integrating sophisticated computational techniques that provide a more rigorous connection between emotional dynamics and ecological as well as biosocial processes. Data assimilation techniques, which combine real-time empirical observations with mathematical models, could help researchers improve parameters related to fear responses, stress-driven behavioral changes, or neural activation patterns. This would make predictions more in line with how things naturally change. These strategies are especially useful for systems where emotional states change quickly and affect operations on many levels, such as choosing a habitat, coordinating a group, or spreading stress signals over social networks, etc. In addition, machine learning methods, such as neural networks, pattern-recognition algorithms, and probabilistic models, offer useful tools for identifying hidden patterns in behavioral data, uncovering links between emotional signals and environmental outcomes, and predicting long-term population or social trends shaped by psychological factors. These techniques could also help create hybrid mechanistic–data-driven models that are better at showing how people's emotional responses differ and how they might vary when they are under chronic stress or fear. Combining these computational methods would not only improve the methods used in this sector, but it would also make it easier to predict the larger effects that emotion-driven interactions have on society and the environment.

The present review has provided a synergetic synthesis of the current state-of-the-art knowledge across ecology, neuroscience, and psychology, focusing on the unifying power of the mathematical modeling approach. It has highlighted the interconnections between these fields and identified promising avenues for future research. Moving forward, interdisciplinary studies that combine ecological field experiments with advanced neurobiological and behavioral analyses provide another important direction aiming at more profound insights into the mechanisms underlying psychological responses, such as fear, and their ecological consequences. Additionally, further exploration of the parallels between animal models and human psychology could lead to novel approaches to treat anxiety disorders and improve mental health outcomes. On the example of fear as an essential psychological response, future research should also focus on developing more integrative models that incorporate individual variation in fear responses and the potential for adaptive responses to chronic fear exposure in both ecological and human contexts.

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