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Applications of Behavioral Economics and Neuroeconomics in Mental Health

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Abstract

Objective: The integration of behavioral economics and neuroeconomics into mental health offers innovative perspectives on understanding and addressing psychological disorders. This overview aims to synthesize current knowledge and explore the implications of these interdisciplinary approaches in the context of mental health.
Method: In this narrative review, we summarized the current evidence regarding the applications of behavioral economics and neuroeconomics approaches in the field of mental health.
Results: Behavioral economics and neuroeconomics provide valuable insights into the cognitive and emotional processes underlying mental health disorders, such as irrational decision-making, impulsivity, and self-control issues. Concepts such as loss aversion, temporal discounting, and framing effects inform the development of innovative interventions and policy initiatives. Behavioral economic interventions, including nudges, incentives, and commitment devices, show promise in promoting treatment adherence, reducing risky behaviors, and enhancing mental well-being. Neuroeconomics contributes by identifying neural markers predictive of treatment response and relapse risk, paving the way for personalized treatment approaches.
Conclusion: The integration of behavioral economics and neuroeconomics into mental health research and practice holds significant potential for improving the understanding of psychological disorders and developing more effective, personalized interventions. Further research is needed to elucidate the mechanisms of action, optimize intervention strategies, and address ethical considerations associated with these approaches in mental health settings.

Key words: *Behavioral Economics; Decision Making; Intervention; Mental Health; Psychiatric Disorders*

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With the increase in the prevalence of mental disorders among different societies and age groups (1-3), we are witnessing an increase in the burden of these diseases on people and health systems (4, 5). For this reason, regular epidemiological studies around the world monitor this important issue and suggest different strategies for managing psychiatric patients. Economic and neuroeconomic theories are one of these solutions that have attracted a lot of attention. Economic and neuroeconomic theories themselves are not direct treatment modalities for managing psychiatric disorders, but they provide valuable frameworks that can enhance our understanding of behavior and decision-making processes relevant to mental health. Neuroeconomics, a dynamic interdisciplinary field situated at the confluence of neuroscience, psychology, and economics (see Figure 1), has garnered increasing attention for its capacity to unravel the complexities of human decision-making (6). Originally conceived to elucidate economic behavior, neuroeconomics has transcended disciplinary boundaries, penetrating deeply into the realm of mental health (7). Its fusion of cognitive neuroscience techniques with economic models has opened new vistas for understanding the neural underpinnings of mental disorders and designing targeted interventions (6). Traditional economic theories often assume that individuals act rationally, maximizing utility. However, behavioral economics incorporates psychological insights, acknowledging that decision-making is often influenced by cognitive biases and emotions. As we delve into this interdisciplinary landscape, we uncover how neuroeconomics offers a novel lens through which to interrogate the cognitive and neural mechanisms underlying decision-making in mental health disorders (8). By delineating the neural circuits implicated in conditions such as addiction, depression, anxiety disorders, and schizophrenia, neuroeconomics provides crucial insights into the altered decision-making processes characteristic of these disorders (9, 10). Through sophisticated neuroimaging techniques such as Transcranial Magnetic Stimulation (TMS) and Magnetic Resonance Imaging (MRI) and experimental paradigms borrowed from economics, researchers have begun to unravel the neural signatures of impulsive behavior, reward processing deficits, and maladaptive choice patterns observed in individuals grappling with mental health challenges (11, 12).

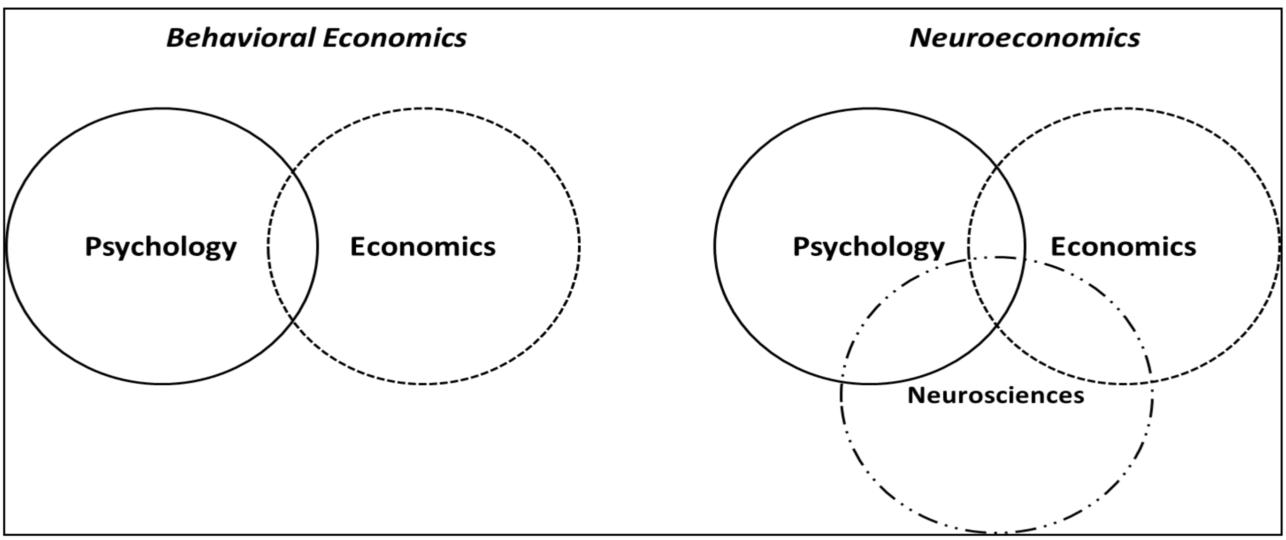

Figure 1. Main Components of Behavioral Economics and Neuroeconomics

Findings from economics can help psychologists and psychiatrists understand how cognitive distortions or biases influence mental health and behaviors. For example, irrational decision-making might be linked to anxiety or depression (13). Moreover, the integration of neuroeconomic principles into clinical practice holds immense promise for optimizing treatment outcomes and enhancing patient care. From developing tailored interventions that target specific neural circuits implicated in addiction cravings (14) to harnessing behavioral economics strategies to promote treatment adherence (15), neuroeconomics offers a repertoire of innovative approaches to mental health intervention (16). Furthermore, by identifying neural markers predictive of treatment response and relapse risk, neuroeconomics holds the potential to usher in a new era of personalized medicine in mental health care (17). Beyond the confines of clinical practice, neuroeconomics also bears profound implications for mental health policy and public health initiatives (18). By elucidating the economic determinants of mental health behaviors and decision-making, neuroeconomics can inform policy decisions related to resource allocation, healthcare financing, and the design of interventions aimed at reducing the societal burden of mental illnesses (19, 20).

In this review, we aim to synthesize the diverse strands of research and practice that converge at the intersection of neuroeconomics and mental health. By illuminating the transformative potential of neuroeconomics in deciphering the neural substrates of mental disorders, shaping targeted interventions, refining treatment approaches, and informing policy decisions, we hope to inspire further exploration and collaboration in this burgeoning field. As we navigate the intricate pathways illuminated by neuroeconomics, we stand poised to unlock new insights and interventions that hold the promise of alleviating the burden of mental illness and promoting flourishing mental well-being in individuals and communities alike.

Behavioral Economics Principles and Decision Making

Reward processing refers to the cognitive and neural mechanisms by which individuals perceive, evaluate, and respond to rewards or positive outcomes (21). It involves assessing potential gains or losses, making decisions based on these assessments, and experiencing pleasure or satisfaction when rewards are obtained (22) (see Figure 2). This concept is central to understanding how people make decisions (23), particularly in the context of behavioral economics and neuroeconomics, where the focus is on how individuals evaluate the costs and benefits of different choices (24, 25). In the context of reward processing, subjective value refers to the personal and individual assessment of how a particular outcome, option, or experience is rewarding or valuable to a person (26). This concept recognizes that the value or reward associated with a choice is not fixed or objective, but varies from person to person based on their preferences, experiences, and current circumstances. For instance, what one person finds highly rewarding, another might find of little value. This subjective evaluation is central to decision-making processes in behavioral economics, where understanding how individuals assign value to different options helps explain their choices and behaviors. Reward Prediction Error (RPE) is a key concept in behavioral economics that describes the difference between expected and actual rewards, driving learning and decision-making (27). When the outcome of an action differs from what was anticipated—whether better or worse—the brain registers this as a prediction error, which then influences future behavior (28). Dopamine neurons play a crucial role in signaling these errors, reinforcing behaviors when rewards exceed expectations and discouraging them when rewards fall short (29). In health behavior, RPE can be harnessed to promote positive changes by providing immediate feedback that creates positive prediction errors, such as instant rewards for engaging in healthy activities like exercise or maintaining a balanced diet. Understanding RPE also has important implications for treating conditions like addiction, where recalibrating the brain's reward system to favor healthier rewards can support recovery and long-term well-being.

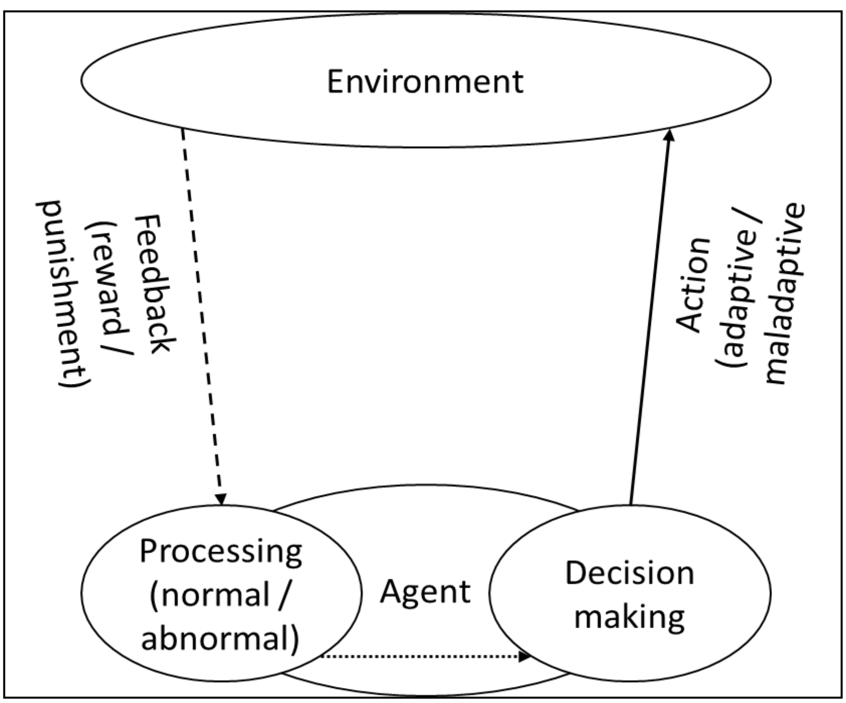

Figure 2. Conceptual Framework of Normal and Abnormal Reward Processing

Costs and discounting are important concepts in economics, particularly in the context of decision-making and behavioral economics (30). Costs refer to the value of what must be given up to obtain something else, encompassing both direct costs, such as monetary expenses, and opportunity costs, which represent the

value of the next best alternative that is forgone. Discounting, on the other hand, involves determining the present value of future costs or benefits, reflecting the common preference for immediate rewards over future ones, known as "time preference" (31). The process of discounting uses a discount rate to convert future values into their present value, with a higher discount rate decreasing the present value of future amounts. These concepts are critical in making intertemporal choices, such as deciding between immediate spending and future savings, and play a key role in behavioral economics by explaining why individuals might opt for smaller, immediate rewards over larger, delayed ones (32).
Reinforcement learning (RL) provides a comprehensive framework for understanding how agents learn and make decisions based on rewards and feedback (33). In RL, agents interact with an environment, performing actions and receiving rewards or penalties, with the aim of developing a policy that maximizes cumulative rewards over time (34). This process aligns closely with reward processing in biological systems, where anticipation of rewards, value estimation, and behavioral adjustment are key (35). Agents in RL learn to predict future rewards, assess the value of actions and states, and adjust their strategies based on feedback, similar to how humans and animals use past experiences to guide decision-making. By balancing exploration of new actions with exploitation of known rewarding strategies, RL mirrors the complex decision-making processes used in real-world scenarios, offering insights into both artificial intelligence and biological learning systems.

Different brain regions play distinct roles in the various aspects of decision-making, including valuation, costs and discounting, reinforcement learning, and reward processing. The orbitofrontal cortex (OFC) is key for evaluating the value of options by integrating sensory information with potential outcomes (36), while the ventral striatum, including the nucleus accumbens, is crucial for processing reward value and is central to the brain's reward circuitry (37, 38). The medial prefrontal cortex (mPFC) (39) and anterior cingulate cortex (ACC) (40, 41) are involved in assessing the costs associated with decisions, such as effort and delay, with the ACC specifically monitoring effort-related costs and conflicts. The posterior parietal cortex (PPC) helps process temporal discounting, evaluating how delayed rewards affect their perceived value. Reinforcement learning is supported by the dopaminergic system, particularly the ventral tegmental area (VTA) and the basal ganglia, which are involved in signaling reward prediction errors and selecting actions based on past rewards. The substantia nigra also plays a role in reinforcing behaviors linked to positive outcomes (42). Reward processing involves the ventral striatum for anticipating and receiving rewards, the amygdala for assigning emotional value to rewards, the insula for processing cravings and risk, and the dorsal anterior cingulate cortex (dACC) for monitoring outcomes and adjusting behavior based on reward expectations (43). Together, these regions coordinate the complex processes that underlie decision-making.

Behavioral Economics, Neuroeconomics and Psychopathology

Atypical reward processing, is increasingly understood as a transdiagnostic characteristic of various forms of psychopathology (44, 45), meaning it is a feature that cuts across multiple mental health disorders rather than being specific to just one (46). As discussed previously, reward processing refers to the way individuals experience, anticipate, and respond to rewards—whether social, material, or emotional. When this process is atypical, it can manifest as either a heightened or blunted response to rewards, or as an inability to properly anticipate or value them. This atypicality in reward processing is not limited to a single diagnosis, but is observed across a wide spectrum of mental health conditions (44). Through a comprehensive search of scientific databases, we identified several high-quality peer reviewed articles that provide aggregated evidence on reward processing deficits across various psychiatric disorders. It is shown that reward processing deficits are a prominent feature of depression, closely linked to anhedonia, or the reduced ability to experience pleasure. Individuals with depression often exhibit a blunted response to positive stimuli, which manifests as decreased motivation and engagement in typically rewarding activities (47). This impairment is associated with reduced dopaminergic activity in key brain regions, including the nucleus accumbens and the prefrontal cortex, which are critical for reward anticipation and valuation (48). Neuroimaging studies reveal diminished activation in these areas during exposure to rewarding stimuli, contributing to the characteristic symptoms of depression. Additionally, individuals with depression may experience impaired reward learning, making them less likely to modify behavior based on positive outcomes, thereby perpetuating negative cognitive and behavioral patterns (49). These deficits not only exacerbate the core symptoms of depression but also contribute to broader functional impairments, highlighting the importance of targeted interventions to enhance reward processing and improve overall functioning in affected individuals.

Reward processing abnormalities in bipolar disorder influence the characteristic mood swings and behavioral patterns associated with the condition. Individuals with bipolar disorder exhibit heightened reward sensitivity during manic and hypomanic episodes, which is linked to hyperactivity in brain regions such as the ventral striatum and orbitofrontal cortex (50, 51). This heightened sensitivity, driven by dysregulation of the dopaminergic system, results in increased risk-taking and impulsive behaviors (50). Conversely, during depressive episodes, reward sensitivity diminishes, contributing to anhedonia and a lack of motivation. Additionally, impaired reward learning in bipolar disorder affects the ability to modify behavior based on previous rewards and punishments, perpetuating maladaptive behaviors across mood states. Reward processing deficits are increasingly recognized as a critical component of anxiety disorders, where individuals often exhibit diminished sensitivity to rewards and heightened sensitivity to potential negative outcomes (52). This dysregulation contributes to the pervasive avoidance behaviors and negative emotional states characteristic of these conditions. Neurobiological evidence suggests that hypoactivity in brain regions such as the ventral striatum and prefrontal cortex underlies the reduced capacity for experiencing pleasure, while exaggerated responses in areas like the amygdala and insula heighten threat sensitivity, further disrupting reward processing (52, 53). These impairments in reward sensitivity and learning hinder the association between positive behaviors and outcomes, reinforcing avoidance and safety behaviors that perpetuate anxiety (54). Understanding these deficits has important implications for treatment, as interventions that enhance reward processing, such as cognitive-behavioral therapy and pharmacotherapy, could mitigate anxiety symptoms by promoting engagement in rewarding activities and addressing the underlying neurocircuitry involved.

Psychotic disorders, particularly schizophrenia, are closely associated with symptoms such as anhedonia, avolition, and impaired decision-making. Individuals with psychotic disorders often exhibit reduced sensitivity to rewarding stimuli and difficulties in reward learning, which contribute to their diminished capacity for experiencing pleasure and motivation (55). These deficits are linked to dysregulation in the dopaminergic system, where hyperactivity in pathways associated with positive symptoms like delusions and hallucinations coexists with hypoactivity in reward-related pathways, particularly within the mesolimbic system (56, 57). Reward processing abnormalities are central to the pathophysiology of addiction disorders, where dysregulation of the brain's reward system leads to compulsive substance use and maladaptive behaviors (58). In addiction, there is a marked enhancement of sensitivity to drug-related rewards, primarily mediated by increased dopamine release in the nucleus accumbens, which reinforces drug-seeking behavior (37, 59). Concurrently, individuals with addiction experience a diminished response to natural rewards, such as social interactions and everyday pleasures, which contributes to the prioritization of substance use over other life activities (60). Moreover, addiction is characterized by impaired reward learning, wherein individuals form strong associations between drug use and positive outcomes despite adverse consequences, perpetuating addictive behaviors (61).

The Principles of Behavioral Economics and Mental Health Care

The integration of behavioral and neuroeconomic principles into mental health care offers innovative approaches to addressing the complexities of human behavior and decision-making (62). Concepts such as loss aversion, temporal discounting, and framing effects provide valuable insights that can inform the development of effective interventions and policy initiatives (63). Additionally, interventions rooted in behavioral and neuroeconomics, including nudges, incentives, and commitment devices, have demonstrated significant potential in promoting adherence to treatment, reducing risky behaviors, and enhancing mental well-being (64-66). By leveraging these insights and techniques, mental health practitioners and policymakers can design strategies that more effectively support individuals in achieving better mental health outcomes (67).

As mentioned above, loss aversion, temporal discounting, and framing effects are key concepts in behavioral and neuroeconomics to explain individual differences in decision making. Loss aversion refers to the phenomenon where individuals tend to prefer avoiding losses over acquiring equivalent gains (68). This principle can be instrumental in designing mental health interventions. For example, framing the benefits of adhering to a treatment plan in terms of avoiding negative outcomes rather than gaining positive ones can be more motivating for patients. Emphasizing the potential losses associated with non-adherence, such as the risk of relapse or worsening symptoms, can increase motivation to stick with prescribed treatments. Temporal discounting is the tendency to devalue future rewards and punishments in favor of immediate gratification (69). This concept is crucial for understanding behaviors related to addiction and other impulsive actions. Interventions that provide immediate rewards for healthy behaviors, such as contingency management programs offering instant incentives for sobriety, can help counteract the effects of temporal discounting (70). By providing immediate gratification for positive actions, these programs encourage individuals to make decisions that benefit their long-term well-being. Framing effects describe how the presentation of information can influence decision-making (71). The same information can lead to different decisions depending on whether it is framed as a gain or a loss. In mental health interventions, framing effects can be used to improve patient engagement and adherence. For instance, framing a health message positively ("Engaging in therapy can improve your quality of life") rather than negatively ("Failing to engage in therapy can worsen your symptoms") can lead to higher acceptance and motivation among patients.

It is also said that interventions rooted in behavioral and neuroeconomics, including nudges, incentives, and commitment devices, have a positive role in enhancing health conditions. Nudges are subtle changes in the environment or the way choices are presented that can significantly influence behavior without restricting options (64, 72). In mental health, nudges can encourage healthier choices and adherence to treatment plans. For example, automated reminders for therapy appointments or medication schedules can help patients stay on track. Structuring choices to highlight the most beneficial options can also lead to better decision-making. For instance, placing healthier food options at eye level in a cafeteria can nudge individuals towards making better dietary choices. Incentives are rewards or penalties designed to motivate specific behaviors. Financial incentives have proven effective in promoting adherence to treatment and encouraging healthy behaviors. Providing monetary rewards for attending therapy sessions, maintaining sobriety, or achieving weight loss goals can lead to improved outcomes (65). Non-monetary incentives, such as public recognition or social rewards, can also be effective in fostering a supportive community environment. Commitment devices are strategies that help individuals stick to their long-term goals by creating constraints that make deviation difficult (73). In the context of mental health, commitment devices can include contracts where patients agree to specific treatment plans and set up penalties for non-adherence. For example, a patient might commit to regular therapy sessions and establish a system where missed appointments result in a donation to a disliked charity. This creates an additional layer of accountability and motivation to adhere to the treatment plan.

The integration of these behavioral and neuroeconomic principles into policy initiatives can significantly enhance public mental health strategies. Public health campaigns that utilize framing effects to promote mental well-being can be more effective in changing behavior. Policies that provide financial incentives for healthy behaviors, such as subsidies for gym memberships or healthy food purchases, can encourage widespread adoption of healthier lifestyles. Furthermore, designing healthcare systems that incorporate nudges, incentives, and commitment devices can improve patient outcomes on a larger scale. For instance, insurance programs could offer lower premiums for individuals who regularly participate in mental health check-ups and adhere to treatment plans. Schools and workplaces can also implement behavioral and neuroeconomic strategies to support mental well-being among students and employees, such as stress management programs that provide immediate rewards for participation.

Limitation

The most significant limitation of this study is the absence of a systematic methodology, which raises concerns about the potential introduction of biases. Without a structured approach to data collection and analysis, there is an increased risk that the findings may be influenced by subjective interpretations or selective reporting, potentially undermining the validity and reliability of the results. This limitation highlights the need for caution when interpreting the study's conclusions and suggests that future research should employ more rigorous methodological frameworks to ensure the robustness of the findings.

Conclusion

The integration of behavioral economics and neuroeconomics into mental health research and practice holds significant potential for improving the understanding of psychological disorders and developing more effective, personalized interventions. Behavioral economics, by examining how cognitive biases and heuristics influence decision-making, provides valuable insights into the maladaptive behaviors often seen in mental health conditions. Neuroeconomics builds on this by linking these behaviors to specific neural mechanisms, thus offering a comprehensive framework that combines both behavioral and biological perspectives. Further research is essential to fully elucidate the mechanisms of action at play. Advanced neuroimaging techniques, such as functional MRI and PET scans, can be utilized to observe brain activity during decision-making tasks, revealing how neural circuits function differently in individuals with mental health disorders. Additionally, computational models can simulate these processes, offering predictive insights and helping to understand how different interventions might modify neural activity and behavior. These tools can help in identifying biomarkers for various mental health conditions, which can lead to earlier diagnosis and more targeted treatments. Optimizing intervention strategies based on these insights is another crucial area of focus. Tailored cognitive-behavioral therapies, for example, can be designed to specifically address cognitive biases identified through behavioral economic analysis. Pharmacological treatments can also be fine-tuned based on neuroeconomic findings to target particular neural dysfunctions. Such personalized approaches promise to improve treatment efficacy and patient outcomes by aligning therapeutic strategies with the individual’s unique neural and behavioral profile. However, the integration of these fields into mental health practice must be approached with careful consideration of ethical issues. Privacy concerns, informed consent, and the potential for misuse of neuroeconomic data are significant challenges that must be addressed. It is vital to establish ethical guidelines and standards to ensure that these innovative approaches are applied responsibly, protecting patient rights and confidentiality while maximizing therapeutic benefits. In summary, the fusion of behavioral economics and neuroeconomics with mental health research represents a promising frontier for understanding and treating psychological disorders. Continued interdisciplinary research, technological advancements, and rigorous ethical oversight will be essential to fully harness the potential of these approaches, leading to more effective, personalized, and ethical mental health care practices.

Conflict of Interest

None.

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