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PSYCHO MACHINA

Discussions on Neuroscience of Decision-Making

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Abstract
Decision neuroscience focuses on the neural mechanisms of the brain involved in decision-making. Researchers in this field observe brain activity in different decision-making conditions to try to understand the fundamentals of decision-making and use this to build models that explain decision-making behavior. Based on the learning and decision neuroscience theory and its research method principle, this paper discusses the basic principle theory of decision neuroscience, analyzes the conditions and characteristics of perception decision and value decision, and probes into the neural biochemical basis of brain decision, including the brain area structure and the mechanism of neurotransmitter's influence on decision. In addition, the research methods of decision neuroscience are further discussed, and the relationship between decision neuroscience and artificial intelligence is discussed, and the future development of the discipline is prospected.

INTRODUCTION

With the development of neuroscience and the progress of brain function measurement technology, decision neuroscience intersecting with economic management, psychology, seriousness and neuroscience has begun to enter the field of decision-making (Serra, 2021). Decision neuroscience is an emerging discipline that studies the decision-making process. It was proposed by many scholars including Professor Baba Shiv of Stanford Business School in 2005, aiming to reveal the activities and neural mechanisms of the brain in the face of different decision-making situations, and to explore how these mechanisms affect individual decision-making behavior (Collins & Shenhav, 2022). This discipline uses neuroscientific research methods such as specific brain injury patient research, neuroimaging and electrophysiological technology to study the neural basis of individual judgment, decision-making and social and market behavior (Srinivasan, 2023). For example, it uses functional Magnetic Resonance Imaging (fMRI) to locate the control of brain processing in individual decision-making, and uses transcranial magnetic stimulation (TMS) and brain injury patient research to clarify the causal relationship between different brain regions (da Silva et al., 2022). Based on the conclusions, a decision model based on neural mechanism is proposed to better understand the decision-making behavior of individuals in real life. Therefore, decision neuroscience provides important implications and guidance for the development of artificial intelligence.

In chapter 2, the basic theories of decision-making are introduced, and the influencing factors and characteristics of perception decision-making and value decision-making are analyzed. Chapter 3 describes the basis of decision-making in the brain. Chapter 4 focuses on the neurotransmitters that play an important role in decision-making, explaining the neural mechanism behind the brain. Chapter 5 summarizes the existing research methods of decision neuroscience, and Chapter 6 discusses the relationship between decision neuroscience and artificial intelligence.

DECISION-MAKING

Decision-making (refers to the process in which people systematically analyze subjective and objective conditions on the basis of mastering a large amount of relevant information and using scientific theories and methods to propose a number of alternatives, analyze the advantages and disadvantages of various alternatives, and select the better one from them (Litvaj et al., 2022). Decision-making is a complex thinking process, which is the process of information collection, processing, and finally making judgments and drawing conclusions (Keith & Ahner, 2021).

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Decision-making is a problem we often face in our daily lives and it involves the evaluation, comparison and selection of different options. The decision-making process is influenced by many factors, including the external environment, intrinsic preferences, emotional states, etc (. How these factors interact to influence our decision-making behavior is an important question for decision neuroscience research. Decision neuroscience is primarily concerned with two types of decision-making: sensory perception-based and value-based decisions.

Perceptual decision-making

Perceptual decision-making is a decision-making method based on perceptual information, which involves the brain's reception, processing and analysis of external environmental information, and the final decision-making process (Ashwood et al., 2022). Perceptual decision-making is a complex process, which is influenced by many factors, including external environment, internal preference, emotional state, etc.

The research on perceptual decision-making involves many disciplines, including neuroscience, psychology, economics, etc. Among them, the research of neuroscience mainly focuses on the role and mechanism of the brain in the process of perceptual decision-making, including the way the brain receives and processes information, and the neural mechanism of the final decision-making (Kelly et al., 2021). The research of psychology mainly focuses on the cognitive process and psychological mechanism of perceptual decision-making, including the cognitive ability, judgment and reasoning process of decision makers (Maksimenko et al., 2020). Research in economics, on the other hand, focuses on the application of perceptual decision-making in areas such as resource allocation and risk management (Jagannathan et al., 2022; Wang et al., 2020).

Perceptual decision-making has a wide range of applications in multiple domains, here are a few of them:

Intelligent manufacturing: In the field of intelligent manufacturing, perception decision-making technology is widely used in industrial automation, intelligent robots, unmanned driving and other aspects (Prat-Ortega et al., 2021). By sensing environmental information, machines can autonomously complete complex workflows and improve production efficiency and quality. Such as autonomous driving, in driverless cars, the perception decision system plays a crucial role (González Rodríguez et al., 2020). By sensing the surrounding environment information, autonomous vehicles can judge the road conditions, the position and speed of vehicles and pedestrians in real time, and make correct driving decisions to ensure the safe driving of vehicles. Figure 1 shows the system architecture of a typical unmanned vehicle (P. Sun et al., 2020). From a technical point of view, the single-vehicle intelligence at this stage can be simply understood as three modules: environment perception, decision planning and control execution.

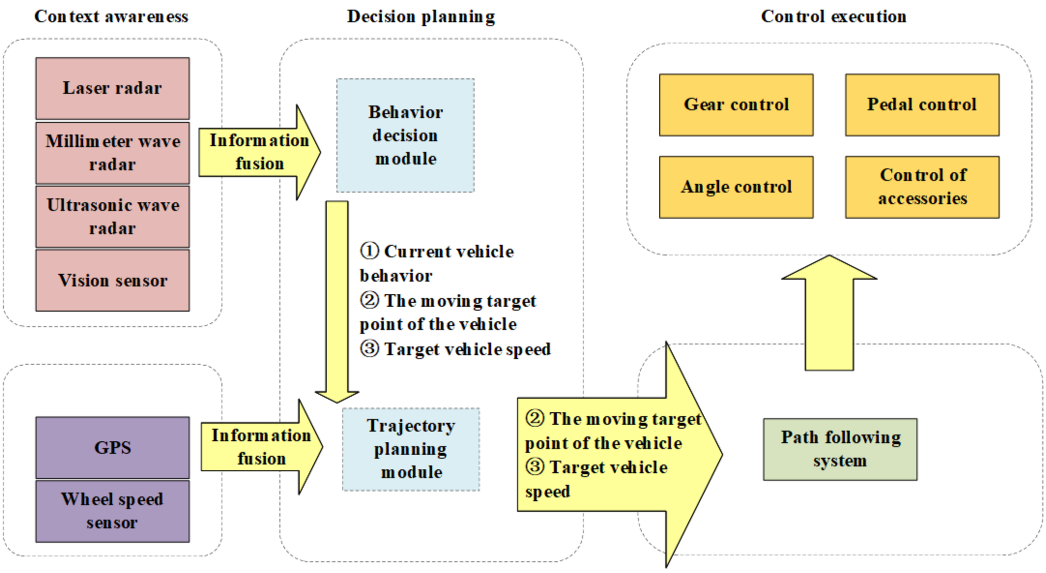

Figure 1 System architecture for autonomous vehicles

The first module is the environment perception module. As the basis of other parts, this module is the prerequisite for realizing automatic driving and plays the role of the "eyes" and "ears" of human drivers. Perception technology uses vehicle sensors such as cameras, lidar, millimeter-wave radar, ultrasound, V2X and 5G networks to obtain multi-source information such as traffic environment information and vehicle status information, which serves for the decision-making planning of autonomous driving vehicles (Mozaffari et al., 2022; Muhammad et al., 2021).

The second module is the decision planning module, which integrates the environment and vehicle information to make the unmanned vehicle produce safe and reasonable driving behavior, and guides the motion control system to control the vehicle (Kiran et al., 2022). The behavior decision system is a narrow decision system, which makes reasonable decisions about the current vehicle behavior according to the information output by the perception layer, and determines the constraints of trajectory planning according to different behaviors (P. Sun et al., 2020). It guides the trajectory planning module to plan the appropriate path, vehicle speed and other information, and sends it to the control layer.

The third module is the control execution module, which is the basis of the autonomous vehicle driving, including the longitudinal control and lateral control of the vehicle. Longitudinal control, namely vehicle driving and braking control, refers to the coordination of the throttle and brake to achieve the precise following of the desired speed, and lateral control, namely the adjustment of the steering wheel Angle and the control of the tire force to achieve the path tracking of the autonomous driving vehicle (Xiao et al., 2022). It is not difficult to see that the decision planning module decomposes the decision-making steps step by step by integrating the understanding of the environment and the understanding of the vehicle's own state, so as to finally guide the car to make reasonable driving actions. This module is also the core of the intelligence of unmanned vehicles (Claussmann et al., 2020).

Smart cities: Sensing decision-making techniques can be used in the construction and management of smart cities (Yigitcanlar et al., 2021). For example, by sensing traffic flow information, urban traffic layout and management can be optimized to reduce traffic congestion and accident risk (Sánchez-Corcuera et al., 2019). Figure 2 shows the block diagram of the smart city perception decision system.

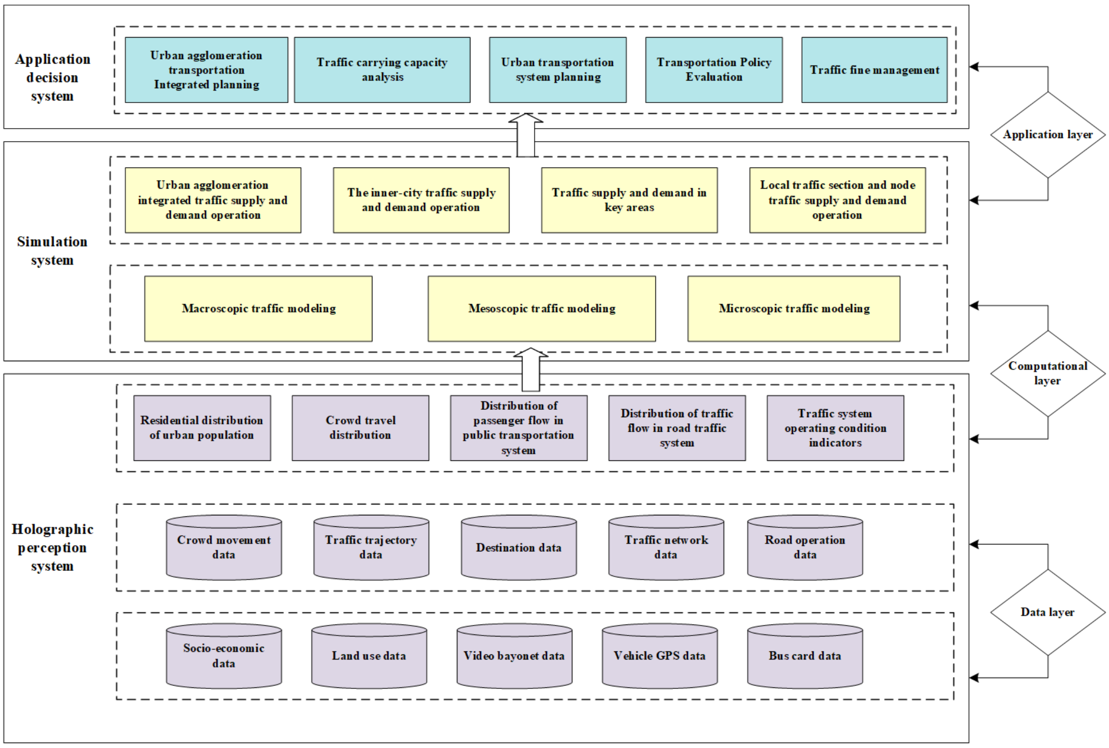

Figure 2 The structure diagram of the smart city decision-making framework

Data layer

The bottom data layer is to construct a multivariate and heterogeneous traffic large database through data collection and fusion processing (Bhattacharya et al., 2022). The database includes the flow data of people and vehicles and the supply and demand operation data of traffic collected from the Internet and mobile phones, as well as the data collected and detected by relevant departments (Bellini et al., 2022; Bhattacharya et al., 2022; Sánchez-Corcuera et al., 2019). The underlying data layer is an important foundation for the holographic sensing system.

Computational layer

The computing layer is based on the data layer, which contains big data intelligent recognition algorithm and traffic simulation model algorithm (Hakak et al., 2020). Among them, the big data intelligent recognition algorithm is to carry out comprehensive perception of urban traffic through data mining, such as the identification of urban population distribution of employment and housing, the identification of the temporal and spatial distribution of crowd travel demand, and the digital representation and feature recognition of various transportation systems (bus network, road network, etc.) operation state (Haque et al., 2022). The algorithm of traffic simulation model is to seek the internal relationship between various types of data and establish a logical deduction algorithm, and build an intelligent operation mode and program of static data input-dynamic data output.

Application layer

The application layer provides different dimensions of transportation supply and demand analysis scenarios, analyzes, applies and displays various types of transportation planning topics, correspondingly supports various types of transportation planning business, and realizes the decision support of the whole technical process of transportation planning (Alsamhi et al., 2019).

Medical domain: In the medical domain, perceptual decision-making techniques can be used for aided decision-making in diagnosing and treating diseases (Knapič et al., 2021). For example, by analyzing the patient's physiological data and condition information, doctors can more accurately judge the type of disease and make treatment plans.

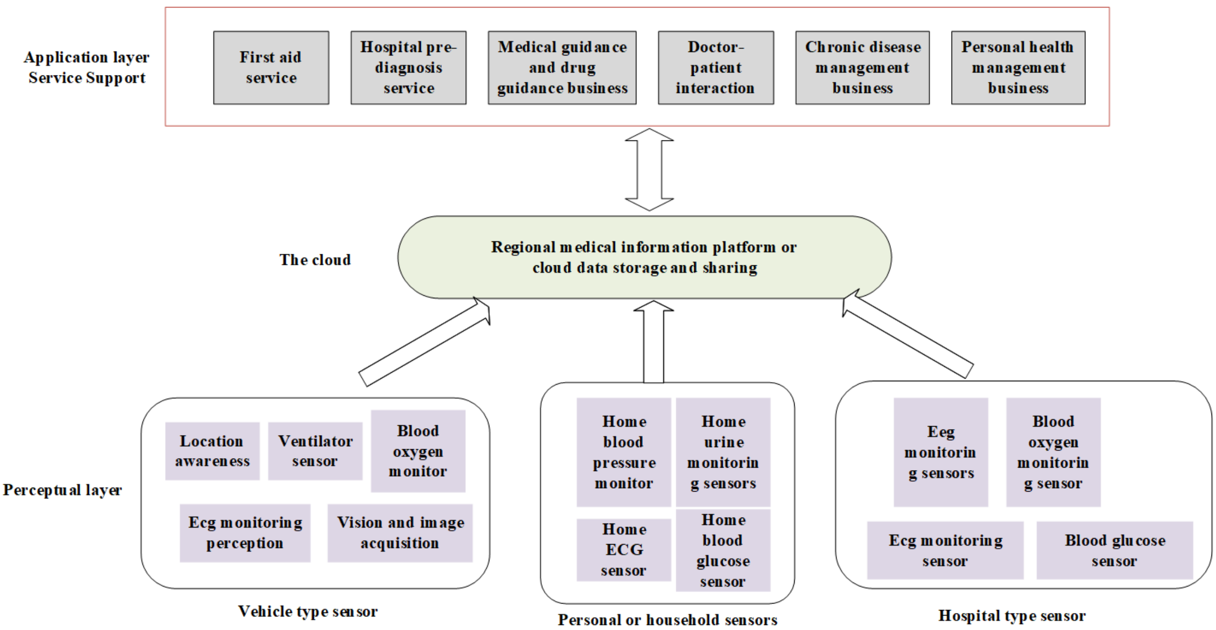

Figure 3 Architecture diagram of intelligent medical perception decision-making system

The architecture diagram of the smart healthcare system is shown in Figure 3. Smart medical treatment involves various key technologies of perception layer, network layer and platform layer in the whole ubiquitous network and Internet of Things system (Begoli et al., 2019). In summary, perceptual decision-making is a complex yet important process that involves several subject areas such as brain, psychology, and economics (Begoli et al., 2019; Cadario et al., 2021; Knapič et al., 2021). The research and application of perceptual decision-making helps us to better understand the way of human thinking and behavior, and also provides important support and guidance for the development of various fields (Hashmi et al., 2020; Lysaght et al., 2019).

Value decision-making

Value decision-making refers to the behavior that an individual chooses according to his or her intrinsic values and preferences when faced with different options (Hashmi et al., 2020). Such decision-making usually requires individuals to evaluate, compare and select options and involves more complex cognitive and affective processes

(Bolam et al., 2019). In the face of problems, setbacks or difficulties, the core idea of value decision-making is to overcome their anxiety, anxiety and pessimism, and make the most reasonable choice or action at that time (Chutia, 2021). This process requires overcoming negative emotions, calming yourself down, and facing difficulties positively. Value decision is not the same as "optimistic", its core idea is: others can do I can do; Now I can't through hard work; I can try what others can't. Maybe I can.

The application of value decision has been reflected in many fields, including enterprise decision, project management, investment strategy, etc.

First, in corporate decision-making, value decisions can be used to determine pricing strategies for products and services, assess the performance of business units and employees, develop and manage budgets, determine the feasibility and priority of new businesses, and assess the social and environmental impact of the business (Lin et al., 2020). Secondly, in project management, value decisions can help to prioritize projects and allocate resources to achieve project objectives (M, 2008). Moreover, in investment strategies, value decisions can guide investors to make investment decisions based on the trade-off between risk and return (Chutia, 2021). Overall, value decision-making is an important management tool that can help companies, projects and investors evaluate and manage their business to ensure that goals are achieved.

FOUNDATIONS OF DECISION-MAKING IN THE BRAIN

Complex decision-making processes stem from the complex structure of the human brain (Coupé et al., 2019). The decision-making mechanism in the brain involves the cooperative work of multiple brain regions, among which the prefrontal cortex, amygdala, hippocampus and other brain regions play an important role (Forde et al., 2020; Nabeeh et al., 2019; Preti & Van De Ville, 2019). The structure of the brain region is shown in Figure 4.

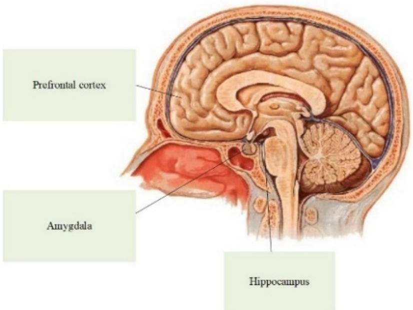

Figure 4 Map of brain regions

Prefrontal cortex

The Prefrontal cortex plays a crucial role in decision-making (Friedman & Robbins, 2022). Located in the front of the brain, it is one of the control centers of the brain, responsible for coordinating and integrating all kinds of information to help us make informed decisions (Reinert et al., 2021). The main functions of the prefrontal cortex include: Executive control: The prefrontal cortex controls and coordinates the activity of other brain regions, ensuring that our actions and decisions are consistent with our goals and intentions (Kenwood et al., 2022). Cognitive control: The prefrontal cortex helps us focus attention, plan actions, suppress impulses, and make decisions. It is also able to process complex information and help us make informed decisions (Preuss & Wise, 2022). Emotion Regulation: The prefrontal cortex is closely related to emotional processing, which can help us regulate emotions, control impulses and anxiety, and thus better cope with challenges and stress (Kolk & Rakic, 2022). During the decision-making process, the prefrontal cortex evaluates different options and consequences by receiving neural signals from other brain regions, and then sends instructions to the body to act (Aoi et al., 2020). It is closely connected to other brain regions such as the amygdala and striatum, which work together to help us make decisions. The role of the prefrontal cortex in decision-making is influenced by many factors, such as an individual's experience, training, and genes (Smith et al., 2019; Tang et al., 2022). Moreover, the activity of the prefrontal cortex is also influenced by substances such as neurotransmitters and hormones, which can modulate the transmission of neural signals and the activity of neurons, thus affecting our decision-making processes.

Amygdala

The amygdala is one of the important brain regions responsible for emotional and social behaviors, and it is closely related to the decision-making process (Gangopadhyay et al., 2021).

The amygdala, whose main function is to process and regulate emotions, is able to detect and identify threats and dangers and react quickly to them (Hu et al., 2021). During decision-making, the amygdala can influence our decision preferences and emotional responses.

On the one hand, the amygdala can provide us with rapid emotional responses that help us assess risks and potential rewards in a split-second (Liu et al., 2020; Y. Sun et al., 2020; Yavas et al., 2019). This rapid emotional response can be very useful in some situations, such as when facing an emergency or threat, where it allows us to make quick decisions and take action.

The amygdala can also negatively influence our decision-making. For example, amygdala hyperactivity may cause us to focus too much on negative emotions and threats at the expense of other, more important information. This may lead us to make overly conservative or riskier decisions (Gangopadhyay et al., 2021).

In addition, the interaction between amygdala and cortex also has an impact on decision-making. The cortex, the brain region responsible for rational thinking and decision-making, can evaluate and adjust the emotional response of the amygdala (Šimić et al., 2021). In the decision-making process, the synergy between amygdala and cortex can help us better balance emotion and rational thinking and make more informed decisions.

Hippocampus

The hippocampus is an internal region of the brain responsible for memory, especially in the processing of spatial and experiential memory (Zhong et al., 2020). It can transform short-term memory into long-term memory, and can link new information with existing memory to form a new memory network. And decision-making is often based on past experience analysis and selection, which requires the participation of the hippocampus (Mattam et al., 2021).

During decision-making, the hippocampus may help us evaluate and compare different alternatives by retrieving past experiences and memories. It may also help us predict possible future outcomes and thus make more informed decisions.

In addition, the hippocampus may also be involved in the execution and evaluation process of decisions. After making a decision, we need to monitor and adjust our behavior to ensure that the desired outcome is achieved (Bolam et al., 2019). The hippocampus may play an important role in this process, helping us remember our decisions, evaluate their effects, and adjust if necessary.

In addition, the brain's neural network system also plays a key role. This neural network involves the interaction of multiple regions in the brain, including multiple regions such as prefrontal cortex, limbic system, and basal ganglia. When we need to make a decision, our brain receives and processes information from our environment and internal states (Chutia, 2021). This information forms a huge neural network through the transmission of electrical signals between neurons, the release of neurotransmitters, and synaptic transmission. With this neural network, we are able to react to our surroundings and make complex decisions.

Cognitive biases can also have an impact on the brain's decision-making during the decision-making process. Cognitive bias refers to the fact that in the decision-making process, there are certain errors in our processing and judgment of information, which leads to the decision results inconsistent with the actual situation. Common cognitive biases include mental account effect, confirmation bias, selection support effect, and so on. The psychological account effect means that people tend to allocate the same funds to different accounts for processing, resulting in less efficient use of funds. Confirmation bias occurs because when we process information, we tend to prioritize information that is consistent with what we already know.

NEUROTRANSMITTERS AND DECISION-MAKING

Neurotransmitters have also been found to play an important role in decision-making (Hodo et al., 2020). Neurotransmitters are chemicals in the nervous system that carry messages, they are released in different areas of the brain and are involved in a variety of cognitive and emotional processes (Wu et al., 2022). This section delved into the complex interplay of neurotransmitters, examining the complex process of how dopamine, serotonin, and GABA (gamma-aminobutyrate) contribute to decision-making (Hampel & Lau, 2022; Niyonambaza et al., 2019; Tavakolian-Ardakani et al., 2019).

Dopamine and Reward Processing

Dopamine is a neurotransmitter closely related to reward mechanism in human brain. The reward mechanism refers to the release of dopamine when an individual performs a certain positive action or receives satisfaction. This release stimulates the reward center in the brain, leading to feelings of satisfaction and pleasure (Hareesha et al., 2022). This is shown in Figure 5. Therefore, dopamine is considered to be a signaling substance that regulates behavior and plays an important role in decision-making.

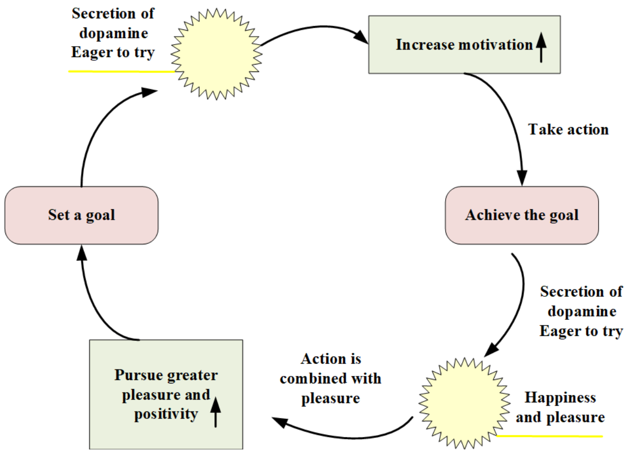

Figure 5 The dopamine reward mechanism

Excess dopamine may cause people to be more risk-taking and less able to assess risk when making decisions. Long-term overproduction of dopamine may lead to problems such as impulsive decision-making and overinvestment, which can have negative effects on individuals and society (Amo et al., 2022).

Dopamine may influence motivation and goal pursuit during decision-making. It is related to reward and motivation, which can motivate people to pursue goals, but at the same time can make people too pursue risk and excitement and ignore risks and consequences. For example, humans are addicted to alcohol, smoking, and even stealing money and shopping (Fisher et al., 2022). They often feel happy when they do these things, mainly because a substance called dopamine in the brain plays a role.

Once exposed to certain dopamine stimulating substances (such as gaming, shopping, drinking, smoking, and even drugs, etc.), it is difficult to control, and if you repeatedly carry out certain behaviors, you may eventually develop to the point where you can't control it, and then want to quit, it is very difficult.

Dopamine may also affect attention and memory. Excess dopamine may cause people to focus too much on immediate, short-term stimuli at the expense of long-term goals and plans (Garritsen et al., 2023). This can have a negative impact on decision making, as the lack of long-term planning and consideration may lead to irrational decisions.

Serotonin and Mood Influence

Serotonin is a neurotransmitter, also known as serotonin, which is found primarily in the central nervous system. Serotonin transmits signals and regulates the function of the nervous system by binding to receptors in the synaptic cleft of neuronal cells (Guzel & Mirowska-Guzel, 2022). It is thought to be related to emotions, motivation, and cognitive functioning.

Serotonin may influence our emotional state and motivation levels during decision making. Studies have shown that changes in serotonin levels may affect our assessment of risk and reward, and thus our decision making (Salvan et al., 2023). For example, we may be more inclined to make risky decisions when serotonin levels are high, while we may be more inclined to make more cautious decisions when serotonin levels are low.

In addition, serotonin may also affect our cognitive abilities. Some studies have shown that serotonin enhances our attention, memory, and learning abilities, which helps us better process information during decision making (Correia et al., 2023). By examining how serotonin levels affect impulsivity, risk aversion, and overall decision quality, we can gain insight into the complex connections between emotions and decision-making processes.

GABA and Inhibitory Control

GABA is an inhibitory neurotransmitter that acts in the brain to inhibit the transmission of nerve impulses. Specifically, GABA transmits information through the formation of inhibitory synapses before neurons, inhibiting multiple neurotransmission activities in the brain (Zhang et al., 2022). This inhibitory effect can coordinate the activity of peaceful and excitatory neurons in the brain to keep the brain in a stable state. GABA can also enhance the flow of potassium ions, thereby inhibiting the electrical activity of brain neurons, effectively reducing the excitability of neurons and reducing the sensitivity of cells to external stimuli (Rizo, 2022).

By inhibiting the activity of neurons, GABA can modulate the neural network activity of the brain, thereby affecting the decision-making process. Studies have shown that GABA plays an important role in decision-making processes. In the face of uncertain situations, GABA release can reduce neural activity in the regions of the brain responsible for decision-making, thereby reducing risk during decision-making (Rizo, 2022). At the same time, GABA can also affect individual motivation and goal pursuit by regulating the release of neurotransmitters such as dopamine, and then affect decision-making.

Understanding the role of these neurotransmitters provides a neurochemical framework for understanding decision making processes (Sarawagi et al., 2021). The delicate balance and interplay between dopamine, serotonin, and GABA helps individuals make delicate choices. By examining the effects of neurotransmitters on reward, emotion, and inhibitory control, this section sheds light on the chemical basis of decision making, providing deeper insight into the intricate interplay between neurochemistry and human behavior.

RESEARCH TOOLS IN DECISION NEUROSCIENCE

In order to gain a deeper understanding of decision neuroscience research, this section provides an overview of the technical approaches to decision neuroscience research (Silva et al., 2022). The research methods of decision neuroscience mainly include observation method, experiment method, modeling method, brain imaging technology and brain stimulation technology (Alsharif et al., 2021).

The observation method is to observe the behavior of the individual in the natural situation to understand the performance and characteristics of the individual in the decision-making process. The experimental rule is to simulate a specific situation by controlling certain variables to observe and compare the situation of different decision results. The modeling principle is to simulate the decision-making process of the brain by establishing a mathematical model or computer model, so as to deeply understand the mechanism and characteristics of the brain when making decisions.

A more direct approach is brain imaging, which scans the brain and looks at the activity of different areas during decision-making. At present, brain Imaging tools have been widely used in the field of decision neuroscience. The main technologies include Electroencephalography (EEG), functional Magnetic Resonance Imaging (fMRI), Positron emission tomography (PET), Magnetoencephalography (MEG), Near Infrared Spectroscopy (NIRS), etc (Yen et al., 2023). A comparison of the various brain imaging tools is shown in

Table I.

Table I Comparison of Brain imaging techniques

Technology	EEG	MEG	fMRI	PET	NIRS
Test object	Electromagnetic signal		Metabolism, Blood oxygen, Blood flow		
Time precision	Millisecond level	Millisecond level	Second level	Second level	Millisecond level
Spatial accuracy	Centimeter level	Centimeter level	Millimeter level	Millimeter level	Millimeter level
Cost of Equipment	35-60w	900-1500w	2000-3000w	2000-3000w	85-230w
Annual operating cost	low	low	85-120w	85-120w	low
Data analysis complexity	More complex	More complex	Very complicated	Very complicated	More complex

Brain stimulation technology: including transcranial magnetic stimulation (TMS), transcranial direct current stimulation (tDCS) and other technologies, can non-invasibly stimulate the human brain to change its functional state, and then study neuronal activity and cognitive processes (.

These research methods can complement each other to better understand the mechanisms and characteristics of the brain in the decision-making process.

RELATIONSHIP BETWEEN DECISION-MAKING AND ARTIFICIAL INTELLIGENCE

The intersection between decision making and artificial intelligence (AI) has become a focus of exploration in an evolving technology landscape. This section delves into the symbiotic relationship between human decision-making processes and AI capabilities.

The contribution of artificial intelligence to decision neuroscience

First, AI can be used to analyze and interpret neuroimaging data, giving scientists a deeper understanding of brain activity and signaling during decision making (. For example, machine learning algorithms (can be used to classify and identify different patterns in neuroimaging data, thus revealing the characteristics of brain activity and signaling mechanisms in different decision-making tasks.

Secondly, AI can be used to build and simulate neural network models to simulate the decision-making process of the brain (. By simulating the connection and signal transmission process between neurons, we can deeply explore the decision-making mechanism of the brain, and test and develop theories and methods in neuroscience.

In addition, AI can be used to design and optimize decision algorithms (. Based on the understanding of the decision-making process in the brain, artificial intelligence can build more intelligent and efficient algorithms to achieve more accurate and fast decision-making.

Finally, AI can help realize the development and application of neuromorphic computing chips. Neuromorphic computing chip is a new type of chip, which can simulate the connection and signal transmission process between neurons, so as to achieve more efficient and low-energy computing (. Such chips have a wide range of applications in decision neuroscience, such as for building more intelligent and efficient robotic systems.

Therefore, artificial intelligence can play an important role in decision neuroscience, providing important support and help for exploring the decision-making mechanism of the brain, optimizing decision-making algorithms, and realizing more intelligent and efficient computing (.

Ethical issues in AI decision-making

When applying artificial intelligence to make decisions, there will be some ethical issues involved, mainly including the following aspects. Data Privacy and Security: AI requires large amounts of data for training and learning, but this also raises questions about personal privacy and data security (. How to balance the relationship between data collection and privacy protection to ensure that personal data is not abused or leaked is an important ethical issue. Algorithmic Bias and discrimination: The training data of an AI system may be biased, leading the algorithm to make unfair decisions or discriminatory behavior toward certain groups or specific groups of people (. This raises fairness and equality concerns and the need to ensure that diversity and fairness are taken into account in the design and training process of AI systems (. Employment and social impact: The development of artificial intelligence may lead to the automation of certain jobs, which brings unemployment problems (. At the same time, artificial intelligence may also have a profound impact on the economy, social structure and social equity. How to deal with the impact of artificial intelligence on employment and society, and ensure social stability and equitable development, is an important ethical challenge. Accountability and transparency: The decision-making process of AI systems is often complex and difficult to explain and understand. This raises questions of accountability and transparency about how AI systems can provide interpretability and traceability so that their decision-making processes can be monitored, evaluated, and held accountable (Leichtmann et al.).

To address these ethical issues, the following measures can be taken: Respect for personal privacy and data security: When collecting and using data, the privacy and security of personal data should be ensured, and necessary measures should be taken to prevent data leakage and misuse (Araujo et al., 2020). Fairness and Diversity: When designing and training AI systems, the diversity and fairness of data should be taken into account, and algorithmic bias and discrimination should be avoided (Whyte, 2022). At the same time, appropriate regulatory measures should be adopted to ensure the fairness and transparency of the system. Safeguarding employment and social stability: When promoting and applying AI, its impact on employment and society should be taken into account, and appropriate policies and measures should be adopted to safeguard employment and social stability (Alam & Mueller, 2021). Increased transparency and explainability: The transparency and explainability of AI systems should be improved so that their decision-making processes can be monitored, evaluated, and held accountable. At the same time, the training and education of relevant personnel should be strengthened to improve their cognition and understanding of artificial intelligence systems (. In general, there is a close connection between decision neuroscience and artificial intelligence, and the two can promote and develop each other. With the continuous progress of technology and the expansion of application scenarios, this connection will be closer and wider.

CONCLUSION

We've harnessed the complexity of the human brain and unraveled the mysteries behind the decisions we make. From the basic elements of brain regions to the neurotransmitters that carry signals, we have gained a deep understanding of the complex network of factors that influence decision-making processes. As we expand our sights to the intersection of decision making and AI, we recognize the significant impact that advanced technologies have on enhancing and shaping our decisions. The integration of artificial intelligence brings opportunities and challenges, and the resulting ethical issues are also one of the issues that must be considered. Taken together, our discussion not only sheds light on the neural basis of decision making. The symbiotic relationship between neuroscience and decision science continues to generate insights that echo across disciplines, from psychology to economics, from ethics to technological innovation. As we stand at the crossroads of the neural frontiers of decision making, the path forward is full of exciting possibilities. Future research efforts promise a deeper understanding of the neural complexity of choice, the development of innovative interventions informed by neuroscience, and responsible AI integration to augment and enhance our decision-making capabilities.

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