Artificial Intelligence Empowering Psychological Research: Current Status, Approaches, and Challenges

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Abstract

Humanity has entered the era of artificial intelligence. Conducting increasingly complex psychological research urgently requires innovative data collection and processing methods. Artificial intelligence and related technologies can facilitate ecological, dynamic, diverse, and precise data collection, are capable of processing massive, multimodal data, and can compensate for the deficiencies of traditional psychological research methods. Therefore, integration with artificial intelligence represents a major direction for the future development of psychology. Simultaneously, in the intelligentization process of psychology, it is crucial not to over-rely on data-driven research methods. Integrating top-down theory-driven and bottom-up data-driven approaches is also essential in intelligentized psychological research.

Full Text

The Status, Approach and Challenges of Artificial Intelligence-Empowered Psychological Research

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Abstract

Humanity has entered the era of artificial intelligence (AI), and conducting increasingly complex psychological research urgently requires innovative data collection and processing methods. AI and related technologies enable ecologically valid, dynamic, diverse, and precise data collection, and can process massive, multimodal datasets, thereby compensating for the limitations of traditional psychological research methods. Therefore, integrating AI represents a major direction for the future development of psychological research. However, in this intelligent transformation of psychology, it is also crucial not to rely excessively on data-driven approaches. The integration of top-down theory-driven and bottom-up data-driven methods is essential for intelligent psychological research.

Keywords: Artificial intelligence; Big data; Multimodal data; Machine Learning; Research Methods

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Psychology is a scientific discipline that investigates human psychological phenomena and their developmental and behavioral patterns. Because individuals exhibit different psychological processes and behavioral manifestations across real-world contexts such as work, family, education, health, and consumption, psychology has gradually formed several sub-disciplines—including industrial and organizational psychology, educational psychology, psychopathology, and consumer psychology—to explore the laws of human psychological activity in various scenarios, making the field both theoretically grounded and highly practical [1].

Contemporary society has entered the information age, and the emergence of AI technology has revolutionized both the content and methods of psychological research. On one hand, AI has profoundly transformed how people live, work, and learn. While enjoying the conveniences brought by AI, humans' psychological trends and behavioral patterns are continuously evolving, making psychological phenomena in AI-enabled contexts an increasingly important research topic. On the other hand, AI has introduced methodological innovations that have advanced the study of human cognitive laws and driven development across psychology, yielding a series of exciting research findings over the past decade.

Although some studies have begun to summarize and analyze AI applications in specific psychological domains, most have focused on individual subfields without systematically reviewing the integration of AI across various branches of psychology. To gain a more comprehensive understanding of the current state of AI-psychology integration, potential issues, and future directions, this paper systematically reviews the intelligent research landscape across psychological sub-disciplines from a macro perspective, identifies key integration points between psychology and AI, and discusses existing challenges to promote further synthesis of psychology and AI technology and advance psychological research.

1. Current State of Intelligent Research in Psychological Sub-disciplines

1.1 Intelligent Development of Brain and Cognitive Neuroscience

The relationship between AI and brain-cognitive neuroscience research is deeply intertwined, with their mutual interaction being crucial for the development of both fields. AI' s primary contribution to cognitive neuroscience lies in brain-computer interface (BCI) technology. BCI refers to the use of electrophysiological techniques to record extracellular electrical activity, thereby enabling communication with the central nervous system (extracellular electrical activity typically results from potential differences carried by ions between neural membranes) [2]. Methods for detecting different types of brain signals can be categorized as invasive or non-invasive [3]. Theoretically, BCI can rapidly observe brain structure and activity and influence brain function by delivering electrical signals to specific brain regions [4], though this remains difficult to achieve in practice. The challenge lies in the fact that while extracellular electrodes can capture vast amounts of brain activity information, this information cannot be effectively decoded, preventing precise judgments about brain activity [5]. This decoding problem stems from our insufficient understanding of the relationship between psychological phenomena and neural activity [6].

AI technology provides assistance in decoding and encoding neural signals [7]. With the development of AI and brain measurement techniques, connecting AI with BCI has been recognized as an important pathway for controlling external devices using EEG signals [8]. For example, Darestani et al. used deep neural networks to process functional Magnetic Resonance Imaging (fMRI) data, dramatically improving imaging precision [9]. Experiments have demonstrated that AI technology can enhance traditional BCI techniques to present images more clearly [10].

Based on research into brain structure and function, neuromodulation represents another major domain in brain science. Neuromodulation technology changes brain function through external stimulation and is currently applied primarily in treating mental disorders and neurological injuries [11]. Both non-invasive and invasive neuromodulation techniques have demonstrated considerable treatment response rates and maintenance of efficacy for mental disorders, particularly unipolar and bipolar depression [12, 13]. However, traditional neuromodulation treatments cannot be personalized for different individuals, suffer from low precision, and cannot deliver high-intensity interventions due to side effects [14]. AI intervention has improved these conditions to some extent.

The Stanford Accelerated Intelligent Neuromodulation Therapy (SAINT) serves as a prime example. SAINT uses intelligent methods to achieve personalized localization of transcranial magnetic stimulation neuromodulation, enabling more precise stimulation treatment for different individuals. With intelligent algorithms, SAINT simultaneously implements 50-minute interval stimulation and high pulse dosage, greatly improving neuromodulation treatment efficiency [15].

Clinical double-blind randomized controlled trials have also demonstrated that SAINT achieves a 78.57% remission rate for depression [16, 17]. SAINT' s success proves the superiority of intelligent neuromodulation technology and points the way forward for future clinical neuromodulation development.

Beyond psychological treatment, AI plays an important role in rehabilitation for patients with neurological injuries. For stroke patients, for instance, many BCI-based treatment strategies have been developed to restore certain functions in affected limbs. Both invasive and non-invasive BCI systems have been used to achieve neural control of prosthetic arms [18, 19]. Invasive BCI allows patients to control movement across different degrees of freedom, enabling more complex and functional movements, though it carries surgical risks. Non-invasive systems, meanwhile, provide only limited control, with most complex movements depending on AI [20]. For example, Nurse et al. used stochastic machine learning techniques to classify motor-related neural signals collected by BCI, achieving 78.9% accuracy in distinguishing neural signals associated with different movements [21]. Importantly, their classifier does not require extensive prior data for BCI training. Their algorithm outperformed other methods on the Berlin BMI IV 2008 dataset and demonstrated high classification accuracy when tested on datasets derived from EEG signals [21]. The development of AI and computer deep learning will provide unprecedented speed in developing new methods for decoding neural signals, laying the foundation for more efficient BCI development.

1.2 Intelligent Social Psychology

Social psychology investigates how individuals' thoughts, emotions, and behaviors are influenced by others and internalized social norms. Social psychologists typically explain human behavior as resulting from mental states and social situations, examining the social conditions under which thoughts, emotions, and behaviors occur and the mechanisms through which these variables affect social interaction [22].

Traditional social psychology research commonly uses self-report scales to study group attitudes and emotions. However, such research demands high participant cooperation, cannot meet timeliness requirements, suffers from memory bias and social desirability effects, and can impose additional burdens on participants [23]. AI-based research on social media provides new solutions to these problems. Measuring users' emotions, cultural values, and behavioral intentions through text and behavioral data generated on social media (such as posts, comments, and replies) has been implemented across multiple countries with different language backgrounds, demonstrating high validity and superiority [24-26]. For example, Chinese researchers analyzed more than 20,000 Weibo posts over four years to examine evolving attitudes toward depression stigma in China. Results showed that while stigma toward depression persisted, social support for people with depression was increasing [27]. Internationally, researchers have also used Twitter, Instagram, Facebook, and Google search data to dynamically monitor group well-being [28, 29].

Beyond group emotions and attitudes, social psychology research also focuses on human behavior patterns. Traditional social behavior research often creates artificial scenarios in laboratories or real environments to explore how different social contexts affect human behavior. Classic studies include Zimbardo et al.' s Stanford Prison Experiment [30], Milgram et al.' s shock experiments [31], and Asch et al.' s line judgment experiments [32]. Such research requires substantial manpower to create scenarios, involves limited numbers of participants, and carries ethical risks [33]. The development of AI deep learning algorithms offers solutions to these problems. Deep learning provides a method for training AI to predict outputs given a set of inputs. While deep learning requires less data preprocessing than traditional machine learning techniques, it demands massive datasets and substantial computing power. With large amounts of data, deep learning models can predict human behavior with considerable accuracy. In the "predict vision" experiment, for instance, after learning from over 600 hours of YouTube videos, a deep learning system could predict 43% of human interaction behaviors, including hugging, kissing, handshaking, or high-fiving [34]. In addition to predicting social behavior, AI has also begun to be used in studying social behavior mechanisms [35]. In future social behavior research, using deep learning technology to learn from large-scale human interaction behaviors will be more widely applied, especially in situations where traditional experimental designs are difficult to implement.

AI is also used to study social psychological mechanisms. For example, Pan et al. examined changes in group emotions during the pandemic context using 105,536 comments on posts from the Weibo account "People' s Daily," specifically analyzing how different factors affected group emotions, including pandemic conditions, fear, and trust in government [36]. By mining big data from the internet through AI technology, social psychology research can provide clues for public policy formulation. For instance, F. Huang et al. studied factors influencing pandemic prevention attitudes by analyzing posting content from 108,914 Weibo accounts during the pandemic [37]. Results showed that strengthening national pandemic awareness through promoting collectivist attitudes was the most effective approach, while increasing fear of the pandemic might have negative effects.

These studies have demonstrated the superiority of big data and natural language processing-based social psychology research in terms of sample size, timeliness, and ecological validity, as well as its potential for translation into social practice.

1.3 Intelligent Consumer Psychology

Consumer psychology, an important branch of social psychology closely related to business behavior, primarily studies customers' processes of selecting, purchasing, using, and discarding products and services. In the business world, consumer psychology research helps companies improve their products, services, and marketing strategies to boost sales, providing important guidance for business operations [38]. The marketing domain is one of the most important application areas for AI [39]. Using AI to predict consumer behavior and propose methods to influence it has gradually become a key development direction for major corporations and consumer psychology research.

With the rise of the internet revolution in commerce, product consumption data has become increasingly easy to record and retain, enabling business managers to develop management strategies that better align with consumer needs through data analysis. However, the massive volume, density, and highly unstructured nature of internet data make traditional data analysis methods difficult to apply. AI algorithms provide an effective approach for analyzing such data. Currently, consumer psychology researchers have begun using AI algorithms to predict consumer behavior, with artificial neural network analysis of customers' internet behavioral data being the most widely applied and achieving promising results [40, 41]. For example, Prasad and Ghosal used artificial neural networks to model big data on consumer behavior and predict purchasing behavior [42]. Yin et al. used AI to analyze data and predict automobile purchasing behavior, finding that AI models achieved 14% higher prediction accuracy than baseline models [43]. These studies collectively demonstrate AI' s important role in consumer psychology research, with findings providing crucial references for product design and marketing strategy formulation.

Beyond consumer behavior prediction, research on factors influencing customer consumption behavior is also a focus of consumer psychology. AI involvement is increasing in areas such as boosting sales, reducing decision-making risks, improving customer satisfaction, and enhancing customer loyalty [44]. With AI technology, companies can collect extensive information to assess customer needs and ensure provision of personalized, high-quality services. AI-powered data analysis also helps e-commerce platforms understand factors influencing purchasing behavior among existing and potential customers [45]. Additionally, with AI assistance, e-commerce practitioners can develop new business ideas to meet consumer needs and keep pace with changing preferences [46]. For example, e-commerce platforms using AI to create user profiles for personalized product recommendations have proven to significantly improve recommendation efficiency [47, 48]. AI-based pricing for target users has also been found to influence judgments about price fairness [49]. Social media content analysis technology can strengthen user segmentation and analysis to determine optimal push strategies for different users or build product brand reputation through online reviews [50].

Furthermore, new sales methods combining AI technology are gradually emerging and have been shown to influence consumer behavior. For example, Kliestik et al. found that shopping with AI assistants can shape consumer behavior [51]. Ameen et al. further explored combining AI technology with virtual reality and wearable devices to improve user experience and thereby influence consumer behavior efficiency [52]. These studies collectively demonstrate AI' s facilitative effects on consumer behavior research and its impact on consumer behavior itself.

1.4 Intelligent Psychopathology

Psychopathology investigates the causes, development, processes, classification, and treatment of mental disorders, playing a crucial role in clinical prevention, diagnosis, and treatment. Traditional psychopathology research requires large-sample, long-term longitudinal studies to demonstrate causal relationships and mechanisms between different factors and mental disorder development [53]. In recent years, AI has brought new developments to psychopathology.

One major AI contribution to psychopathology concerns genetic research. Psychopathology research uses polygenic risk scores to simultaneously study the combined effects of multiple genes on mental disorders and analyze genetic risks for various conditions including depression, anxiety, and bipolar disorder [54, 55]. However, these methods cannot study the effects of genetic variation outside protein coding, thus limiting advancement of genome-wide psychopathology. Using AI machine learning technology, Xiong et al. constructed a computational model that takes DNA sequences as input and applies general rules to predict gene splicing in human tissues. The model provides highly accurate in silico predictions of sequence variants' effects on pre-mRNA splicing, including their impacts on various human pathologies. This model can be used to study various mental disorders and identify consequences of common, rare, and even spontaneous genetic variations. In this study, the AI computational model predicted autism through gene splicing variants with 85% accuracy [56]. Based on AI algorithms, researchers have also begun to model the formation mechanisms of mental disorders including intellectual disability (ID), autism spectrum disorder (ASD), epilepsy, and broader neurodevelopmental disorders more comprehensively by combining genetic influences and neurophysiological markers, enabling more accurate predictions [57].

Beyond genetics, AI technology has also revolutionized mental health detection methods. Mental health detection combining AI with Electronic Health Records (EHR) overcomes limitations of traditional longitudinal studies such as single time-point data collection, promising more precise mental health diagnosis [58]. EHR-based approaches enable personalized measurement based on different health records for different participants, rather than measuring all participants' mental health status simultaneously. Therefore, compared to traditional detection methods, combining AI technology with EHR for mental health measurement is more dynamic, comprehensive, and accurate. Traditional mental health analysis modeling typically relies on labor-intensive work such as expert analysis, resulting in models with limited generalization ability across different datasets or populations [59]. Based on large EHR datasets, deep learning algorithms can reveal more generalizable associations between pathological factors [58]. For example, Nemesure et al. used deep learning technology to analyze EHR and study the predictive effects of healthcare-related indicators on depression and anxiety [60]. Researchers have also used long-term EHR data to identify predictive indicators of self-harm behavior [61, 62], improving suicide behavior prediction accuracy to 85% [63]. These successes continuously demonstrate the superiority of using AI technology to analyze scattered EHR data for psychopathology research.

Meanwhile, beyond traditional predictive indicators, natural language indicators such as participants' daily language and written texts have been incorporated into mental disorder prediction indicators. Through joint modeling of EHR and natural language indicators, researchers have broadly predicted 46 psychological symptoms, achieving 87% prediction accuracy in patients with severe mental illness [64]. Beyond EHR-based research, researchers have also used natural language processing technology to study people' s mental health status through natural language big data on social media platforms [65]. On platforms like Twitter and Facebook, researchers have used natural language processing to analyze posting content to predict various mental disorders for over a decade, finding that negative emotional language on Twitter closely correlates with official U.S. suicide statistics [66, 67]. In recent years, researchers have also used natural language processing technology to extensively monitor mental health through Instagram social media data [68]. On the Weibo platform, researchers measured users' domestic violence experiences and mental health status, discovering multiple mental health impacts of domestic violence experience, including high depression tendency, suicidal ideation, and low life satisfaction [69]. During the COVID-19 pandemic, researchers also used Weibo data to monitor group mental health and analyze factors affecting it [70]. Multiple studies have demonstrated the feasibility of using social media big data and AI natural language processing technology for mental health monitoring and studying mental disorder formation mechanisms [71].

1.5 Intelligent Psychometrics

Psychometrics is a research area in psychology concerning measurement theory and techniques, aiming to measure unobservable latent constructs including intelligence, personality, mental disorders, and educational achievement. Based on individual test performance and questionnaire responses, psychometrics infers these latent constructs through mathematical models comprising multiple indicators [72].

Traditional psychometrics often relies on paper-and-pencil or computer-based psychological tests to measure traits, widely applied across various contexts such as the Big Five personality test [73], PHQ-9 depression screening scale [74], and Stroop task for measuring cognitive flexibility. However, current test forms have several limitations. First, self-report scales are commonly used to assess mental health, personality, and attitudes. Self-report scales depend on participants' self-evaluation, which often does not completely reflect reality [75]. For items requiring recall of life scenarios, participants'responses are also affected by memory bias [76]. Additionally, in high-stakes contexts like occupational selection or when answering questions about non-mainstream social attitudes, participants are often influenced by social desirability bias, leading to conscious or unconscious false responses [77]. Second, traditional cognitive measurement often uses highly structured test tasks that are disconnected from real problem-solving scenarios, resulting in low ecological validity and inability to accurately predict real-life performance [78, 79].

Using AI to assess individual psychological traits based on real-life data represents an important means to overcome traditional measurement limitations. Currently, preliminary research on using big data for personality measurement has been conducted primarily in computer science. By combining psychological theory to construct prediction models, this emerging research method has extracted many big data predictors of psychological traits from various data sources. For example, using the Twitter platform, Wald et al. used machine learning to predict users' Big Five personality types from profile information [66]. Beyond social media data, smartphone usage data can also be used for psychometric measurement. For instance, Jacobson et al. used deep learning algorithms to merge social activity data and movement data recorded by smartphones for dynamic monitoring of social anxiety, achieving 70% accuracy [80]. Beyond smartphones, using AI algorithms for multimodal data extraction and analysis is also a major recent trend. For example, using intelligent voice analysis technology, Polzehl et al. used voice characteristics to predict Big Five personality, with results highly consistent with target personality types [81]. Beyond voice, facial recognition can provide different indicators for psychometrics. Researchers have used AI algorithms to extract muscle activity and facial contour information from individual facial videos to analyze expression changes and model depression diagnosis [82], while prediction models combining voice and facial features achieved 90% accuracy for post-traumatic stress disorder diagnosis [83]. Additionally, combining virtual reality (VR) technology with IoT technology, researchers can measure cognitive abilities through multimodal data in more ecologically valid scenarios. For example, Plotnik et al. combined VR, cognitive measurement paradigms, and motion capture data to conduct high-ecological-validity multimodal assessments of executive function [84]. These studies all point the way forward for intelligent psychometrics development.

2. Key Integration Points Between Psychology and Artificial Intelligence

Psychology is an empirical science. In the AI era, data storage and analysis methods have expanded psychology' s data radius and enriched methods for mining patterns from data. Therefore, in the intelligent development of any psychological sub-discipline, integration with AI proceeds from two angles: data collection and data analysis, showing similar developmental paths. Below we detail the key integration points between psychology and AI in data collection and analysis; current intelligent psychology research has made breakthroughs in one or more of these integration points.

2.1 Intelligent Psychological Data Collection

Data collection is a crucial process in psychological research. With the rapid development of sensing technology, AI research has extended to diverse real-world scenarios, allowing psychological data collection to move beyond traditional reliance on laboratory settings or self-report questionnaires. In intelligent psychological data collection, more effort is invested in how to collect data more precisely in more ecologically valid ways. With the assistance of intelligent algorithms, data collection in both virtual scenarios and real-time daily life monitoring has become possible, with significant improvements in data collection precision and richness.

2.1.1 Virtual Reality Technology Virtual Reality (VR) technology can construct more realistic scenarios for psychology, helping address limitations of traditional measurement paradigms. Using realistic scenarios and intelligent algorithms to analyze participants' behavioral data collected during tasks, researchers can increase participants' arousal levels in measurement environments while maintaining control over distracting stimuli. For example, researchers have used VR technology to conduct Go/no-go and Stroop tasks in virtual apartments and driving scenarios [85, 86], test cognitive flexibility in virtual beach settings [87, 88], assess planning and prospective memory in virtual shopping scenarios [89], and conduct multitasking tests in virtual city environments [90]. However, although such studies replicate real scenarios, the measurement paradigms remain variations of traditional laboratory paradigms, with insufficiently lifelike measurement content and suboptimal ecological validity. To address these issues, some teams have used VR to design more lifelike measurement methods. For instance, the Besnard team used various steps in coffee making in a virtual kitchen to measure participants' executive function [91]. Gong Yan' s team at Wenzhou University designed three virtual urban scenarios to measure spatial cognitive ability through realistic city walking processes [92]. Building on this, more complex VR scenarios have been developed that can measure multiple cognitive abilities within the same lifelike scenario. For example, the Virtual Reality Functional Capacity Assessment Tool (VRFCAT), approved by the U.S. FDA in 2019, uses lifelike tasks in VR scenarios to measure 12 different cognitive abilities [93]. Beyond cognitive measurement, VR technology can also be applied to other psychological trait measurements. For example, De-Juan-Ripoll et al. used virtual reality scenarios to simultaneously record participants' behavioral and physiological indicators during scenario interaction to predict Big Five personality traits related to risk decision-making [94]. Dechant et al. also measured social anxiety symptoms through interaction characteristics between participants and virtual characters in VR scenarios [95].

These studies continuously demonstrate the feasibility of using VR technology to develop more ecologically valid psychological trait assessment systems. However, VR use also introduces new problems. For example, VR-based measurement has higher learning difficulty compared to traditional paradigms, which may reduce participants' performance [96]. Second, existing VR measurement systems remain immature in human-computer interaction—for instance, some VR actions still require mouse or joystick completion [91], reducing measurement validity. Additionally, VR cognitive measurement increases assessment duration [89]. Overly long measurement times increase participant fatigue and boredom, causing attention decline and cognitive fatigue that distort assessment results. Future research should therefore propose further solutions to these problems from experimental design and hardware development perspectives.

2.1.2 Real-Life Behavioral Data Recorded by Smartphones With the popularization and iteration of technological products, data from people' s daily lives has become increasingly easy to record and retain, offering potential to improve the ecological validity of psychological trait measurement. Chittaranjan et al. began using Nokia phones in 2013 to study how smartphone app usage preferences could predict Big Five personality [97]. With the development of intelligent algorithms, the usage data that smartphones can record has become increasingly rich. For example, Ai et al. used smartphone GPS location data to determine daily spatial behavior patterns and predict Big Five personality [98]. A Princeton University research team further assessed users' Big Five personality using six indicators from smartphones: social behavior, music consumption, app usage, mobility, overall phone usage frequency, and day-night usage ratio, achieving 40% accuracy [99]. Beyond personality measurement, using smartphone-retained data for mental health monitoring also achieves high accuracy. For example, Jacobson et al. used deep learning algorithms to merge social activity data and movement data recorded by smartphones for dynamic monitoring of social anxiety, achieving 70% accuracy [80]. Additionally, an increasing number of apps targeting mental disorders have emerged, some of which have been proven effective in clinical trials for monitoring or improving symptoms of certain mental disorders, including anxiety, stress, alcohol abuse, sleep disorders, depression, suicidal behavior, and post-traumatic stress disorder [100].

2.1.3 Brain Activity Signal Data Enhanced by Intelligent Algorithms Brain science has become increasingly important in psychology, with researchers demanding higher precision and efficiency in EEG and brain imaging. Due to individual brain differences, AI algorithms' correction of brain imaging results provides crucial support for psychological research. During brain signal acquisition, internal parameters of collection tools continuously provide information to AI algorithms, including pulse duration and amplitude, stimulation frequency, device energy consumption, stimulation or recording density, and electrical properties of neural tissue [101]. Upon receiving this information, AI algorithms can identify useful parts and logic in the data while simultaneously generating expected functional outcomes [7].

Furthermore, molecular neuroimaging has advanced significantly based on deep learning algorithms, with convolutional neural networks—a subset of deep learning—being most widely used in intelligent brain imaging. In brain imaging using Positron Emission Tomography (PET) and Single Photon Emission Computed Tomography (SPECT), machine learning algorithms can improve imaging quality, reduce scanning time, and classify imaging for different diseases in neurodegenerative disorders [102]. For example, researchers have used convolutional neural networks to enhance PET brain imaging, significantly improving image denoising and quality [103-105]. Deep learning algorithms also enable image completion for PET brain imaging with missing data [106]. Beyond PET imaging, AI also assists Magnetic Resonance Imaging (MRI). In intelligent fMRI research, Multivoxel Pattern Analysis (MVPA) is considered a promising machine learning technique, currently used primarily to study information contained in distributed neural activity patterns to infer functional roles of brain regions and networks [107]. Brain activity pattern recognition and neurofeedback (DecNef) decoding based on MVPA algorithms also lay the foundation for more precise determination of brain activity patterns [108]. Meanwhile, AI technology can improve fMRI imaging speed by extracting less data, increasing efficiency. Using AI reconstruction technology in brain imaging allows subjects or patients to experience faster imaging processes with reduced likelihood of image interference from subject movement, while hospitals and researchers can shorten waiting times to accommodate more patients or collect more data while maintaining imaging quality [15]. From current trends, intelligent brain imaging will become increasingly operationally feasible in practical applications. In future research, AI algorithm participation in brain imaging may gradually become mainstream.

2.1.4 Comprehensive Sensory Data Based on IoT and Wearable Devices Traditional psychological data collection methods can only collect relatively single types of data, rarely combining behavioral data with physiological or neurophysiological indicators for comprehensive analysis, resulting in insufficiently accurate measurement of psychological traits. Internet of Things (IoT) technology provides solutions for integrating multiple data types. IoT refers to technology where objects with sensors, processing capabilities, software, and other technologies connect and exchange data with other devices and systems through communication networks [109], providing methods for simultaneously collecting multiple data types on the same timeline. With IoT development, researchers have begun attempting to measure psychological traits through multiple sensors. For example, in cognitive assessment, Debie et al. used IoT technology to simultaneously measure eye movement and EEG data to more accurately measure cognitive load [110]. Additionally, real-time monitoring of teaching through IoT makes educational evaluation more dynamic and in-depth. For example, Goldberg et al. collected gaze, head posture, and facial expression data to monitor each student' s attention level in real-time during instruction in classroom environments [111]. In future research, using IoT technology to collect multimodal data in real-time during tasks for multi-faceted assessment of psychological traits is also a direction toward more precise psychological assessment systems.

Concurrent with IoT development, wearable devices further provide more ecologically valid multimodal data measurement methods for psychological data collection. Currently, wearable device applications in psychology are primarily in mental health. Intelligent wearable device applications can provide rich data types for mental health assessment in daily life, including heart rate variability, skin conductance, and movement data. Heart rate variability and skin conductance level are important indicators for measuring individual stress status [112, 113] and have proven effective for measuring mental disorder levels [114, 115]. For example, Kleiman' s team developed the Empatica E4 smartwatch to monitor and predict suicidal ideation in real-time by collecting skin conductance and heart rate data, with experiments proving its feasibility for daily life use [116, 117]. By collecting movement data through smart wearable devices, researchers have also achieved dynamic monitoring of mental disorders including depression and ADHD [118, 119]. These intelligent mental health monitoring technologies can not only monitor individual mental health status in real-time in daily life, guiding individuals to seek professional help promptly when at risk for mental disorders, but also have potential as auxiliary diagnostic components in clinical diagnosis, providing daily mental health data to improve diagnostic accuracy. Meanwhile, physiological data measured by wearable devices also has potential benefits in cognitive psychology research, such as real-time monitoring of stress status and other indicators affecting cognitive ability during tasks, while physiological indicators like heart rate variability can also reflect cognitive function. For example, higher high-frequency heart rate variability is associated with better cognitive performance, while lower high-frequency heart rate variability is associated with cognitive impairment, making heart rate variability a reliable indicator of cognitive function [120, 121]. In future intelligent psychological research, how to use IoT and wearable devices to collect multimodal data for more precise extraction of psychological indicators is also a major development direction.

2.2 Intelligent Psychological Data Analysis

Data analysis is also a crucial component of psychological research. In psychology' s intelligent transformation, increasing evidence shows that AI plays an important role in expanding data analysis methods for psychological research. Deep learning technology provides powerful support for psychologists in data analysis. By attempting to simulate human brain behavior to "learn" from massive data, deep learning has profoundly impacted many data analysis applications, including speech recognition, image classification, computer vision, and natural language processing [122]. AI technology applications in psychological research also enable extraction of information that human experts cannot identify from data, providing more detailed indicator variables for psychological research.

2.2.1 Data-Driven Research Supported by Big Data AI development has benefited from rapid data accumulation. Big data is characterized by large volume, high variability, diverse types, high value, and authenticity [123]. Well-known big data scenarios include social media such as Facebook, Twitter, and Weibo [124]. Such data is created in real-time and increases daily, primarily appearing as text, images, videos, and documents. Additionally, Electronic Health Records used in psychopathology research also belong to the big data category. Big data mining and analysis technology is used to process massive data that cannot be handled by traditional database analysis techniques. Through big data analysis, intelligent psychological research has generated new research models. In traditional psychological research, researchers often use theory-driven methods to explain empirical data (i.e., how things happen) rather than merely describing them (i.e., what happened). Theory-based approaches increase psychologists' understanding of causal relationships in psychological processes and underlying mechanisms of social phenomena. However, with the emergence of big data research using machine learning and other data-driven methods, psychology research has also begun adopting bottom-up, data-driven approaches to predict human behavior or traits [125].

Early big data research in psychology focused primarily on massive text data accumulated on social media, allowing psychologists to predict psychological indicators and group phenomena through large volumes of internet posting content. For example, Zheng et al. analyzed 1,813,218 Weibo posts from 2010 to 2019 to study attitude changes toward homosexuality in China, finding that Weibo users increasingly supported and accepted homosexual rights over the decade [126]. Through text analysis and coding of 108,914 Weibo posts, Xu et al. measured eight emotions including joy, anticipation, love, anger, anxiety, disgust, sadness, and surprise, and developed an emotion dictionary, laying a foundation for subsequent social media big data emotion research [127]. These studies demonstrate the practicality of big data in bottom-up psychological trait prediction. Alongside big data prediction, due to big data' s dynamic recording characteristics, big data mining technology can also help study development trends of psychological factors. For example, Tung and Lu studied the impact of public events on population depression symptom development trends through natural language processing [128]. In Weibo-based research, Cheng et al. used text analysis technology to analyze 600,000 Weibo posts and studied group happiness in relation to COVID-19 pandemic timeline changes, discovering significant effects of living environment on happiness that were stronger during the pandemic [129]. Beyond social media data, deep learning algorithms based on Electronic Health Records can also reveal associations between pathological factors that are difficult to discover using traditional data analysis methods [58]. For example, Nemesure et al. used artificial neural networks to analyze big data from Electronic Health Records, discovering impacts of medical and physical health indicators on depression and anxiety [60].

2.2.2 Text Data Analysis Based on Natural Language Processing Technology Natural Language Processing (NLP) primarily studies interaction between computers and human language, particularly how to program processing and analysis of large amounts of human language data [130]. Text analysis technology in NLP can convert unstructured text data into meaningful data for subsequent analysis [131]. Psychologists previously had weak text analysis capabilities, limited to manual thematic analysis with results often affected by subjective bias [132]. Analyzing text content through NLP text analysis technology can largely avoid subjective bias. Additionally, natural language analysis focuses not only on meaningful content in text but also on analyzing participants' language expression patterns or vocabulary choices to reflect latent psychological variables that traditional psychological tests cannot accurately capture. For example, Sumner et al. used NLP technology to analyze language use characteristics in users' Twitter posts to predict users' Dark Triad personality traits [133].

In natural language analysis, Latent Semantic Analysis (LSA) also plays a significant role in psychological research. LSA aims to explore latent relationships behind words, analyzing them based on usage context rather than dictionary definitions [134]. Due to LSA' s characteristic of discovering latent information, it shows great potential for measuring relatively implicit, latent psychological traits. For example, Kwantes et al. asked participants to write based on different scenarios, used LSA to analyze writing content, and predicted participants' Big Five personality traits [135]. Through LSA of online discussion content, Dasigi et al. also measured participants' implicit attitudes [136].

2.2.3 Psychological Trait Analysis Integrating Speech Data Beyond language content, speech intonation can also reflect individual psychological traits [81]. Traditional speech analysis primarily involved manual extraction of speech spectrum parameters for further statistical analysis, whereas AI speech analysis technology can incorporate more refined speech variations and more diverse speech characteristics into analysis compared to traditional methods, providing more detailed and rich results for psychological research. For example, Guidi et al. used AI speech analysis technology to analyze speech fundamental frequency and voice quality, finding significant correlations with Big Five personality [137]. Speech analysis algorithms are also gradually being applied in clinical mental disorder monitoring. Researchers use speech analysis algorithms and audio recognition devices to collect participants' speech information in clinical environments, modeling speech rate, pitch, and coherence features to identify depression and bipolar disorder with 73.33% accuracy [138, 139]. Building on this, using deep learning algorithms to learn large amounts of mental disorder patient interview data can further improve depression identification accuracy using speech data [140]. However, speech is easily influenced by factors such as discourse content, subsequently affecting personality prediction accuracy [137]. Future research requires more refined speech feature extraction to identify indicators less affected by discourse content.

2.2.4 Psychology Research Driven by Computer Vision Technology Computer vision is another important AI domain. Through image recognition technology, AI can provide visual information that humans cannot carefully distinguish for psychological research and predict psychological traits through visual information analysis. Currently, extensive visual analysis in psychology includes facial recognition, posture analysis, action analysis, and eye movement analysis.

The connection between facial features and psychological traits has been confirmed in previous traditional psychological research [141]. Visual analysis technology makes facial feature analysis more detailed. For example, Setyadi et al. used artificial neural networks to analyze facial features to predict four basic personality temperament types (sanguine, choleric, melancholic, and phlegmatic) [142]. Kachur et al. assessed participants' Big Five personality using artificial neural networks to analyze 31,367 photos from 12,447 participants [143]. However, although these experiments continuously demonstrate the feasibility of using AI to analyze facial features for personality assessment, current assessment accuracy is insufficient for practical application. Future research needs to refine facial features to improve assessment accuracy.

Gait recognition is another application of visual analysis in psychology, primarily used in mental disorder measurement. For example, by analyzing mental disorder patients' gait data using AI algorithms, Zhao et al. distinguished anxiety and depression patients with 64%-74% accuracy [144]. T. Wang et al. distinguished depression patients from normal participants through gait data with up to 93.75% accuracy [145].

Additionally, eye movement data analysis is a commonly used method in current psychological research. Eye movement data has been regarded as an effective measurement indicator for basic cognitive functions such as working memory [146] and attention [147], and is also used to measure some composite or higher-order cognitive functions [148, 149]. Using deep learning algorithms, researchers have achieved autism diagnosis based on eye movement data [150]. In educational monitoring, Deng and Wu also used deep learning algorithms to analyze students' eye movement fixations, achieving real-time monitoring of learner attention during instruction [151]. Additionally, visual analysis algorithms can be used to process human interaction videos for social behavior research. In the "predict vision" experiment, for instance, after learning from over 600 hours of YouTube videos, a deep learning system could predict 43% of human interaction behaviors, including hugging, kissing, handshaking, or high-fiving [34].

2.2.5 Multimodal Data Fusion Modeling and Analysis AI technology enhances psychology' s ability to analyze different data types, making collaborative modeling by merging multiple data types possible. In multimodal data collaborative modeling analysis, convolutional neural networks can achieve feature alignment across different data types, establish mapping relationships between multimodal features, and perform feature fusion on multimodal data. In practical applications, combining IoT wearable device data, AI algorithms can simultaneously process multimodal data including voice, text, and physiological indicators collected by wearable devices for modeling analysis, achieving more accurate prediction of psychological traits [152]. In cognitive function prediction, multimodal data comprehensive modeling enables more precise evaluation of cognitive levels. For example, Niemann et al. used deep learning algorithms to combine skin conductance and traditional cognitive ability measurement paradigm task completion for more precise measurement of participants' cognitive impairment levels [153]. Plotnik et al. also achieved precise assessment of executive function by combining cognitive measurement paradigms and motion capture data for modeling [84].

Compared to traditional self-report evaluation, using convolutional neural networks for multimodal data modeling can also minimize self-report bias to the greatest extent, improving assessment efficiency while ensuring good measurement precision. For example, in personality measurement, researchers used convolutional neural networks to comprehensively model eye movement data, skin conductance data, and behavioral data in VR tasks, achieving 75.4% personality prediction accuracy [94]. In mental disorder measurement, prediction models combining voice and facial features achieved 90% accuracy for post-traumatic stress disorder diagnosis [83]. In psychotherapy response rate prediction, AI-based multimodal data modeling also shows great promise. For example, Fleck et al. merged fMRI and H-MRS data to predict short-term response rates to lithium medication in bipolar disorder with 80% accuracy [154]. Merging depression levels, demographic indicators, PTSD comorbidity, and neuroticism symptoms data to predict antidepressant medication response rates in depression patients achieved 71% accuracy [155]. Brodey et al. combined multiple clinical indicators to predict treatment outcomes in schizophrenia patients with 76.5% accuracy [156]. Additionally, comparative studies have demonstrated that multimodal data modeling combining multiple neuroimaging, genetic, and clinical indicators achieves higher accuracy in predicting treatment effects for specific patients [157].

3. Challenges and Limitations

3.1 Limitations of Data-Driven Research

Although a series of experiments have demonstrated the feasibility of using AI and big data technology to study psychology, relying solely on bottom-up data-driven approaches may also produce biased results. Currently, most intelligent psychology research is still conducted from a technical perspective within computer science, with relatively few studies led by psychology researchers. Consequently, a major problem with most current research is the lack of research hypotheses and experimental designs from a psychological theory perspective. Such deficiencies may lead to inadequate control of relevant variables during data collection, low signal-to-noise ratios, and poor research result credibility and replicability. For example, Mitchell et al.' s study of population happiness through Twitter produced biased conclusions due to inadequate control of relevant demographic variables [158]. Another example is Ginsberg et al.' s development of a virus spread prediction model using machine learning to select 45 search terms from 50 million Google search records [159]. However, researchers later found that the model completely missed non-seasonal influenza, indicating it predicted seasonal rather than actual flu trends [160]. This typical case shows that relying entirely on data-driven approaches is insufficient for correct research conclusions; top-down theory-driven approaches are indispensable in psychological research.

In future research, researchers should collect data based on rigorous psychological theories and research designs to increase signal-to-noise ratios and enhance data value. During data analysis, targeted analysis and mining should also be conducted based on specific research hypotheses. That is, within psychology' s research framework, big data collection and analysis methods should be introduced rather than directly applying AI analysis methods to solve psychological research problems. For example, Elragal and Klischewski proposed a lightweight theory-driven approach to big data analysis that protects the analysis process from biases that purely data-driven research may cause while giving data mining some freedom. In lightweight theory-driven big data analysis, heavy theoretical commitment can be appropriately avoided during data collection to give AI certain freedom for data collection beyond existing theory [161]. However, data induction, cleaning, and analysis should rely on validated knowledge systems and existing theoretical foundations to transcend purely quantitative analysis methods. Finally, a theoretical framework should be used to standardize big data analysis to guide the selection of big data analysis methods and techniques. The choice of analysis methods should be based on given data, clear research questions, and model assumptions. Without theoretical framework guidance, analysis technique selection may be based primarily on tool availability, researcher experience bias, stakeholder friendliness, etc., leading to distorted research conclusions. Meanwhile, compared to traditional laboratory research, big data heterogeneity allows researchers to control more theoretically relevant variables such as time, location, or population density. Therefore, merging theory-driven and data-driven experimental designs should be the future direction in intelligent psychology research.

3.2 Sample Bias in Big Data Research

Due to the lack of necessary sample design in big data research, many big data research samples currently suffer from bias. Although big data far exceeds traditional research sample sizes in volume, it is not equivalent to the subject population and may still contain sample bias. For example, discourse on social media may only appear on social media platforms [162], and active versus inactive internet users themselves differ in psychological traits. Additionally, different social media platforms limit sample characteristics, preventing samples from reflecting the overall population [163]. Beyond this, data bias in big data research also affects results in terms of analysis methods. For example, Electronic Health Record data generation is often supervised, making generated data biased toward prediction targets. Additionally, the fact that deep learning models currently cannot explicitly capture uncertainty poses challenges for data and label transfer learning, making models less robust when dealing with changes in underlying data distributions [164]. While using deep learning to predict human social behavior is feasible, this method is limited by data. Due to lacking data on extreme or scenario-specific behaviors, this method for studying human social behavior is currently confined to daily behavior aspects, while special social-psychological behavioral phenomena still require traditional social behavior experimental designs. These are also problems that future research needs to address.

4. Conclusion and Future Directions

The emergence of new technologies and analysis methods has brought new directions to psychological research, along with a series of related problems. For example, speech analysis technology provides possibilities for speech-based psychological trait analysis, but currently remains difficult in solving the dependency between speech features and speech content [137]; future research requires more refined speech feature extraction to identify indicators less affected by discourse content. Using AI to analyze facial features for personality assessment is feasible, but current assessment accuracy is insufficient for practical application; future research still needs to refine facial features to further improve assessment accuracy. Using VR technology to develop more ecologically valid cognitive ability assessment systems is feasible, but VR-based measurement has higher learning difficulty that may reduce participants' performance [96]; existing VR measurement systems remain immature in human-computer interaction [91]; device limitations also reduce measurement validity; additionally, overly long VR assessment duration also affects results [89]—these are all problems that VR assessment research needs to address in the future.

With the development of cutting-edge technologies, the trend toward psychology intelligentization has gradually emerged, with AI integration becoming increasingly tight across various psychology research domains. In data collection, AI technology has revolutionized psychology data collection methods. More ecologically valid and interactive VR experimental paradigm data, daily behavior data collected via smartphones and wearable devices, brain imaging enhanced by intelligent algorithms, and real-time multimodal data based on IoT technology are becoming increasingly preferred analytical data for psychology researchers. In data analysis, AI deep learning algorithms have greatly expanded psychology research data analysis modes and efficiency. Beyond traditional analysis methods, deep learning algorithms, natural language processing technology, speech analysis and visual analysis algorithms for audio-video data, and convolutional neural network multimodal data modeling for fusing multimodal data are gradually being used to solve psychology research problems.

The revolution in data collection and analysis methods has already brought new developments to psychology research, solving many psychology problems that were difficult to answer with traditional methods. Although many problems remain in current AI applications in psychology, including over-reliance on data leading to distorted research conclusions and lack of necessary sampling design leading to biased data samples, it is foreseeable that with further integration of psychology and AI and sufficient refinement of intelligent psychology research paradigms, research across all psychology domains can achieve substantial progress.

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Note: Figure translations are in progress. See original paper for figures.