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RESEARCH ARTICLE

Teaching Psychology in Era of Digital Intelligence: The Role of Artificial Intelligence in Knowledge-Oriented and Research-Oriented Education

Feng Yu[a], Yijun Zhao[a], Liying Xu[a], Kaiping Peng[b]

[a] Department of Psychology, Wuhan University, Wuhan 430072, China

[b] Department of Psychological and Cognitive Science, Tsinghua University, Beijing 100084, China

Abstract Empowered by the rapid advancement of digital technologies, including Big Data, artificial intelligence (AI), and virtual reality, human society has transformed from the era of information to the era of digital intelligence. Unlike previous social formations, the digital-intelligent society has disrupted many long-held consensus norms and introduced numerous difficult challenges. To cultivate adaptive talents with general literacy of digital intelligence and specific professional competences, psychology, as one of the foundations of social sciences, must launch a revolution in future-oriented education. In higher education, the two principal components, defined by their nature and objective, are knowledge-oriented and research-oriented teaching. The former is designed to provide an introduction to the fundamental principles and basic knowledge of psychology for freshmen and sophomores, while the latter is intended to equip junior and senior undergraduates with the skills necessary for conducting scientific research. First, it is both possible and necessary to integrate AI throughout the processes of knowledge-oriented teaching. In this article, we propose a "loop model" to demonstrate the applications of AI in the knowledge-oriented phase. Furthermore, to provide a reference criterion for nurturing innovative and research-oriented students, we present a theoretical framework of "chimeric research" to provide a comprehensive overview of psychology research in the era of AI. In conclusion, psychology education needs to be aligned with the demands of the modern society and embrace digital intelligence in both knowledge- and research-oriented teaching phases.

Keywords digital intelligence, artificial intelligence, psychology, knowledge-oriented, research-oriented

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Liying Xu (✉)
E-mail: liyingxu@whu.edu.cn

1 Educational Challenges in the Era of Intelligence and Digitalization

What is education? Jaspers (1991) poetically depicted the essence of education, positing that "education is a tree shaking a tree, a cloud to promote a cloud, a soul awakening another soul." In his view, education is a process oriented toward humanity, facilitating spiritual growth and individuals' development into "whole persons" with fully developed personalities and spiritual dimensions. Regarding higher education, Jaspers (1959) asserted that universities were institutions dedicated to the pursuit of truth, embodying three critical functions: research, dissemination of knowledge, and cultural education. The significance of higher education lies in guiding students to uncover their potential and strengths, helping them discover their authentic selves, imparting cultural heritage and legacy, and cultivating their ability to investigate the diverse phenomena of the real world. Jaspers' perspective underpinned the modern educational paradigm, which centers on human beings and aims at their free development. In terms of specific content, the focus of education is essentially on "learning." The principles of educational psychology represent various interpretations of the learning process. From trial-error connectionism of Thorndike (1913), classical behaviorism of Watson (1913), and operant conditioning of Skinner (1938), to social learning theory of Bandura (1986), the fundamental assumptions of modern educational psychology transcend the notion of human as a passive recipient, increasingly emphasizing the agency of learners. Therefore, it can be argued that modern education is an activity oriented toward nurturing humanity, shaping souls, and awaking agency.

Within the fields of humanities and social sciences, psychological science occupies a significant position. Psychological research is inherently focused on human beings, encompassing all aspects of human existence within its purview. It seeks to uncover the objective principles that govern the subjective realm of human experience. In its pursuit of scientific rigor, psychology aspires to emulate the methodological framework of physics, aiming to establish laws that systematically explain psychological phenomena. From a problem-oriented perspective, during the celebration of its 125th anniversary, *Science* (2005) unveiled 125 of the most challenging scientific questions, among which issues such as consciousness, memory, cooperation, mechanisms of dreaming, language acquisition, addiction, autism, moral concepts, and cultural roots await resolution through psychological research. Given the discipline's nature and mission, the American Psychological Association (APA) (2023) formulated the *APA Guidelines for the Undergraduate Psychology Major* (hereinafter referred to as *the Guidelines*) to standardize the fundamental objectives of psychology education. The Guidelines delineate the goals of undergraduate psychology education into five components: "content knowledge and application," aimed at introducing key concepts, principles, and theories of psychology and presenting the fundamental framework and context of the discipline; "scientific inquiry and critical thinking," emphasizing the mastery of basic norms and skills in psychological science research; "values in psychological science," highlighting the cultivation of a psychological perspective and social responsibility; "communication, psychological literacy, and technical skills," focusing on developing individuals' capacity to influence the world through expression; and "personal and professional development," dedicated to fostering self-regulated, proactive, and fully developed individuals.

According to the outcome-based education (OBE) theory, an ideal educational mode should establish objectives based on anticipated outcomes and, subsequently, construct each component of the educational system to facilitate the achievement of these objectives by every student (Spady, 1994). Compared to the traditional educational model, the OBE mode offers several advantages, including clarity of goals, flexibility in pathways, ease of comparison, and enhanced student engagement (Tam, 2014). Guided by the OBE theory, we reinterpreted and reframed *the Guidelines*, as shown in Figure 1. In the OBE mode, outcomes are a vital concept. For higher education, educational outcomes should encompass both the mastery of basic knowledge and the acquisition of advanced research capabilities. Concurrently, educationalists often distinguish between two analogous dimensions in the teaching process and academic research. Anderson (2005) categorized the educational process into four progressive stages based on the classification of knowledge: factual knowledge, conceptual knowledge, procedural knowledge, and meta-cognitive knowledge. The first two stages focus on imparting fundamental content within a discipline, transforming students from novices to proficient individuals. The latter two stages aim to cultivate their ability to independently expand their knowledge, fostering their potential to become experts rather than remaining novices. Similarly, Boyer et al. (2015) divided academic research into two analogous parts: scholarship of interpretation, which aims to elucidate existing knowledge, and scholarship of discovery, which seeks to expand new understanding. Based on these theories and models, we categorized the five objectives proposed by the APA into two learning phases. The first phase, termed the knowledge-oriented teaching phase, primarily targets lower-level undergraduate students, focusing on the cultivation of foundational knowledge, scientific attitudes, and value orientations. The objective of this phase is to develop students' understanding and interest in psychology, enabling them to grasp and apply psychological principles effectively. The second phase, termed the research-oriented teaching phase, is designed for upper-level students, aiming to cultivate them into academic professionals capable of conducting psychological research. The objective of this phase is to impart research thinking and academic skills to students, facilitating their personal and professional growth. This framework delineates the underlying logic of psychology education and has become a widely recognized gold standard in the field.

As the era of digital intelligence, dominated by artificial intelligence (AI), draws near, the rapid advancement of technology is poised to disrupt long-standing societal norms while simultaneously presenting new opportunities for the field of psychology education. In this new era, humanity faces a profound challenge: The rise of AI will threaten to erode the unique status of human intelligence. The power and potential impact of AI extend far beyond its capacity to

Note: Blue represents knowledge-oriented teaching, while red represents research-oriented teaching

Figure 1 Reframing of *the Guidelines*.

replace human labor and automate processes across various sectors, including industrial production (Yang et al., 2021), management (Parent-Rocheleau & Parker, 2022), content creation (Eshraghian, 2020), and medical diagnosis (Varghese et al., 2024). These advancements pose tangible threats to human resources and safety (Yogeeswaran et al., 2016). In particular, AI has the formidable potential to reshape societal cognition, exacerbating existing biases within society (Glickman & Sharot, 2025) and contributing to the erosion of interpersonal relationships (Granulo et al., 2024). Moreover, the ongoing evolution of AI is set to alter human self-perception by redistributing the relative importance of various human capabilities, thereby accentuating those that remain uniquely human and beyond AI's current reach (Cha et al., 2020; Santoro & Monin, 2023). In summary, AI's impact on human society is a double-edged sword: While it significantly enhances social productivity and liberates human labor (Noy & Zhang, 2023), it also catalyzes a transformation in societal cognition and structure, potentially leading humanity to lose its bearings within the technological realm.

Such transformations have also posed significant challenges and crises to the psychology education system. First, AI has redefined the template for talent demanded by society, necessitating that education, as a critical supply side, reevaluate its approach to cultivating adaptive and future-oriented talents. Within the realm of psychology, the rise of AI has generated numerous social impacts that remain to be fully examined and understood. Psychologists are thus compelled to investigate the origins and development of these AI-related social impacts and formulate targeted intervention strategies. Second, the widespread adoption of AI has enhanced the accessibility of information and improved the availability of knowledge. This shift requires psychology education to refocus its efforts, moving from a simplistic emphasis on knowledge acquisition to a more complex emphasis on capability development. In summary, the digital intelligence era has highlighted the critical need to cultivate adaptive and interdisciplinary talents. For knowledge-oriented teaching, AI technologies can be integrated into various aspects of the teaching process to enhance the efficiency and quality of knowledge dissemination and acquisiton. Additionally, for research-oriented teaching, AI not only catalyzes a shift toward intelligent scientific research paradigms but also introduces new practical issues that traditional research must address.

To effectively navigate the challenges posed by the digital intelligence era, a comprehensive framework is essential for systematically organizing AI-integrated psychology education. This framework should maximize the benefits of AI while minimizing its potential negative impacts. To this end, we propose two distinct models, each tailored to the unique demands of the knowledge- and research-oriented stages of education. These models serve as valuable references for educators in this evolving field. In the knowledge-oriented stage, we introduce the "loop model," which provides a structured approach to analyzing the role of AI in teaching. This model not only elucidates the multifaceted contributions of AI but also offers practical strategies for leveraging its strengths while mitigating its weaknesses. By doing so, it aims to optimize AI's integration into the educational process. In the research-oriented stage, we define the emerging interdisciplinary field of "AI + psychology" as a "chimeric research" framework. This innovative framework identifies and explores two novel types of cross-disciplinary studies, each addressing the unique aspects of the intersection between AI and psychology. We advocate that educators incorporate the corresponding skills and thought processes associated with these new research paradigms into their practical teaching, which can equip students with the tools needed to thrive in this dynamic field.

2 Knowledge-Oriented Psychology Education: A "Loop Model"

Vygotsky (1978) posited that children's development and learning were processes of constructing "scaffolding." He argued that individual development occurs through traversing the zone of proximal development from existing levels of knowledge to potential developmental heights (Vygotsky, 1978). This learning perspective is equally applicable to lower-year undergraduate education. For freshmen and sophomores, acquiring foundational knowledge in their field of study is fundamentally a process in which teachers provide "scaffolding" to support their learning. However, learning is not a passive act of absorption; it requires individuals to actively engage in "climbing the scaffolding" and transcending the zone of proximal development. Correspondingly, education is not merely a process of indoctrination; rather, it requires fostering students' initiative and their capacity for self-regulation. Self-regulation refers to the dynamic process through which individuals set a desired goal, take actions to achieve that goal, and continuously monitor their progress (Carver & Scheier, 1998; Inzlicht et al., 2021). Therefore, education can be conceptualized as a self-regulatory activity in which individuals exert efforts toward a particular learning goal, overcoming personal inertia and difficulties along the way, and ultimately, attaining the desired outcome. Especially in knowledge-oriented teaching, students are expected to master fundamental knowledge and skills, which represent their potential developmental area, while their current knowledge and abilities define their present state. The process of knowledge acquisition is, therefore, essentially the process of surpassing the zone of proximal development. To further understand how self-regulation operates during learning and goal attainment, we turn to Carver and Scheier's (2012) negative feedback loop model, which explains the mechanics of self-regulation. In this model, an individual's current state is set as the input function of the loop, which is then compared to a pre-established reference value through a comparator. The result of this comparison constitutes the output function of the loop, reflecting the discrepancy (whether higher, lower, or equal) between an individual's current state and the reference value. According to this model, individuals inherently strive to reduce the gap between the input and reference values. Therefore, when the current state falls below the reference value, adjustments to environmental factors are necessary to recalibrate the input value, initiating a new cycle of comparison until the input value exceeds the reference value (Carver & Scheier, 1982). Carver and Scheier's theory closely mirrors the test-operate-test-exit model of Miller et al. (1960), with the core principle being the continual adjustment of an individual's current state to align with pre-set standards, facilitated through constant feedback. This theory elucidates the process of self-regulation as an adjustment process centered around the comparator, where an individual's agency is expressed in altering extrinsic factors after a comparison failure, thereby modifying the input function and comparison results.

When applying the feedback loop model of self-regulation to the context of education and learning, we can refine the model to construct an educational feedback loop (see Figure 2 below), which can serve as a blueprint for designing AI applications in teaching. In the proposed educational feedback loop model, knowledge-oriented learning consists of five essential components:

Knowledge acquisition: Students acquire specific knowledge through the instruction provided by the teacher.

Comparator: The process of comparing the student's current level of knowledge acquisition with the pre-set standard.

Standard: The pre-established learning goals and knowledge mastery levels that must be achieved.

Assessment: An examination that operationalizes the virtual comparator.

Pass: Attainment of the final goal.

Overall, the operational mode of the educational feedback loop model mirrors that of the original model. In knowledge-oriented teaching, students' current mastery of knowledge is compared to an ideal standard, and through assessment, individuals are encouraged to improve their proficiency until they reach the required level of "pass."

We examined the application of the loop model to frame and plan the integration of AI in knowledge-oriented teaching. First, during the knowledge acquisition phase, AI can serve as the driving core of digital teaching assistants. Traditional knowledge-oriented teaching models are constrained by time and space, requiring instructions to be completed within designated periods and locations. AI-powered digital teaching assistants transcend these temporal and spatial limitations, offering students more convenient access to knowledge services. Bibliometric research has shown that using educational robots in the classroom as assistants or tools can significantly enhance student engagement and interactivity, thereby improving knowledge mastery (Guo et al., 2024). Thus, we recommend that educators develop knowledge maps for core psychology courses and train corresponding digital assistants to complement teaching tasks. Students can leverage their free time to interact with digital assistants, acquiring knowledge at their own pace and according to their mastery level.

Second, in the context of setting standards, AI can be used to design personalized teaching plans

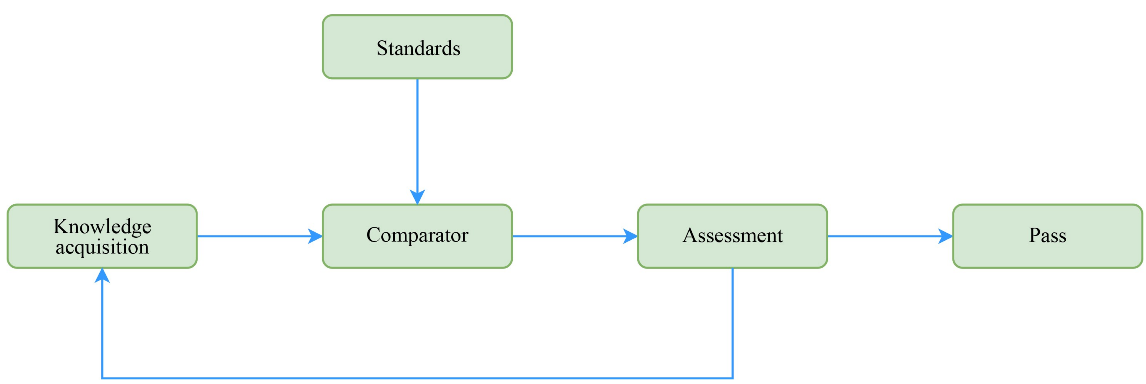

Figure 2 Loop model of AI-empowered psychology education.

centered on individual students. Traditional psychology education typically applies uniform learning objectives to all students to ensure educational fairness. However, with AI assistance, teaching objectives can be personalized, thereby fostering a student-centered, process-oriented learning environment (Fortner & Katzarska-Miller, 2024). AI algorithms can collect and analyze students' historical learning records, test scores, study habits, and interests, providing a comprehensive understanding of their knowledge levels and learning needs. Based on these data, AI can help formulate tailored learning goals. According to the "scaffolding" theory of Vygotsky (1978), the width of the proximal development zone is a critical factor influencing learning outcomes. Learning goals should neither be too simplistic, as this could diminish students' interest in exploring the unknown, nor excessively challenging, which might fail to stimulate intrinsic motivation. AI's comprehensive information and precise predictive capabilities offer adaptive, real-time, and self-paced learning opportunities, facilitating personalized education. Each student can find a learning path best suited to their needs (Tapalova & Zhiyenbayeva, 2022; Tong & Hu, 2024). Thus, we suggest that teachers use AI to assess the prior knowledge levels of each student, thereby formulating specific learning objectives and plans. These plans can be used by teachers to integrate the academic situations of all students to design the teaching outlines and content. Meanwhile, students can refer to the personalized plans suggested by AI and, upon completing the standardized curriculum, engage in targeted supplementary learning.

Additionally, AI's real-time interaction and dynamic analysis can serve as the comparator. In traditional education, the comparator is a virtual and hypothetical psychological process that continuously drives the self-regulation of learners. However, with the digital transformation of education, both standards and knowledge acquisition have become quantifiable data, allowing the comparator's function to be maximally realized. AI-powered intelligent tutoring systems can track students' learning progress in real time, compare existing data with personalized standards, identify gaps in knowledge acquisition, and provide timely, targeted feedback (VanLehn, 2011). For example, the use of AI chatbots significantly enhances students' learning motivation, efficacy, interest, and performance while reducing academic anxiety (Wu & Yu, 2024). In terms of specific implementation, we propose that teachers adjust their approaches to students in a timely manner based on the academic performance data provided by AI and in combination with their own understanding of each student's personality, abilities, and attitudes. The AI comparator eliminates the negative impacts on students' interpersonal and psychological health caused by social comparison. Instead, it allows individuals to compare themselves with their own previous stages, thereby achieving personal development and progress.

Finally, AI can be applied in the assessment phase to automate and refine academic evaluations. Unlike natural sciences, which rely on mathematical derivation, psychology depends heavily on students' comprehension and processing of knowledge rather than simple formulaic calculations. Thus, standardized, objective quantitative testing presents significant challenges. AI-driven assessment systems aim to address this issue by digitizing the test content and providing automated, precise evaluations. These systems can automatically collect and evaluate data, yielding results comparable to those of human evaluators (Ouyang et al., 2023). In fact, in tasks such as writing assessments and revisions, automated writing systems have been shown to outperform teacher feedback (Liu et al., 2025). Thus, we suggest that teachers learn and become proficient in using AI-based academic assessment systems to provide timely feedback. Meanwhile, AI assessment systems should enhance their interactive features based on assessment and feedback. By leveraging the communication capabilities and knowledge base of large language models (LLMs), these systems can achieve advanced functions such as interpretation and intervention.

3 Research-Oriented Psychology Education: A "Chimeric Research" Framework

For upper-year undergraduates and graduate students, it is insufficient to merely teach psychological knowledge and its application; they must also master the fundamental methods and paradigms of scientific research. In the era of digital intelligence, AI has sparked a new scientific revolution (Leslie, 2024). This revolution has also significantly impacted psychology (Grossmann et al., 2023; Xu et al., 2024), compelling research-oriented education to undergo transformation in order to cultivate research talent capable of adapting to the changing times. However, the following questions remain: How can we cultivate innovative research talent in the age of AI? What new research paradigms must be taught? These questions are yet to receive systematic considerations and responses. We argue that the issue of talent cultivation fundamentally hinges on the complementary role of AI in psychological research. To answer the question of what kind of talent to cultivate, it is essential to first consider the nature of the research that needs to be conducted. By clarifying how AI influences psychological research, the question of talent development can be more effectively addressed. Therefore, we must first explore how AI has altered psychological research; in other words, what constitutes "AI psychology?" AI psychology is an interdisciplinary field that integrates AI with psychology. To more clearly delineate the scope and types of AI psychology, we propose a "chimeric research" framework (see Figure 3 below). We contend that AI psychology is essentially a "chimera," a direct fusion of two distinct disciplines that gives rise to two distinct models. The first model, AI for psychology, focuses on the use of new AI technologies in addressing traditional psychological research problems. The second model, AI of psychology, places more emphasis on psychology itself, treating AI as the subject of psychological research. This model uses traditional psychological research methods and paradigms to investigate AI and the new challenges it introduces. Below, we explore these two models of AI psychology in greater detail and offer insights and suggestions for research-oriented education.

"AI for psychology" refers to the application of AI algorithms to enhance traditional psychological research methods and paradigms, achieving an intelligent upgrade without altering the core content of psychological research. The process of psychological research can be simplified into the following steps: literature review, hypothesis formulation, hypothesis testing, and results presentation (see Figure 4 below). We will now explore the various applications of AI within this process. Initially, generative AI can accelerate the literature review process by understanding the content of research papers and generating literature reviews based on specific

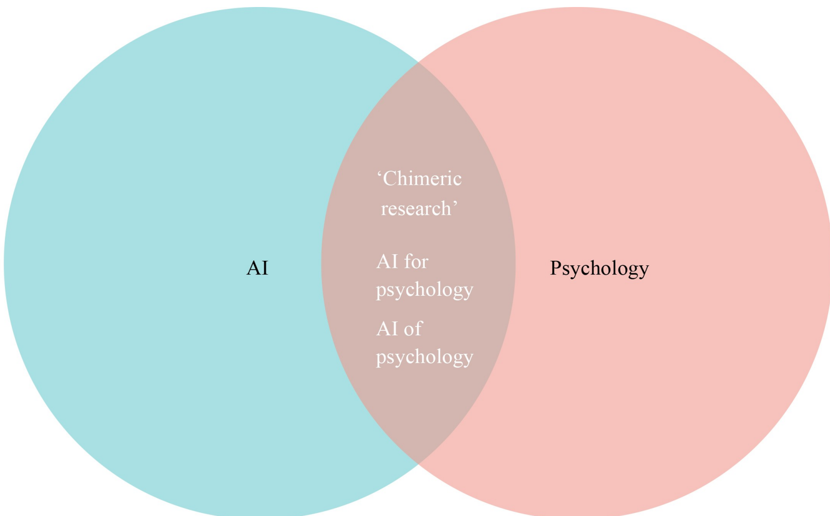

Figure 3 "Chimeric research" framework of AI psychology.

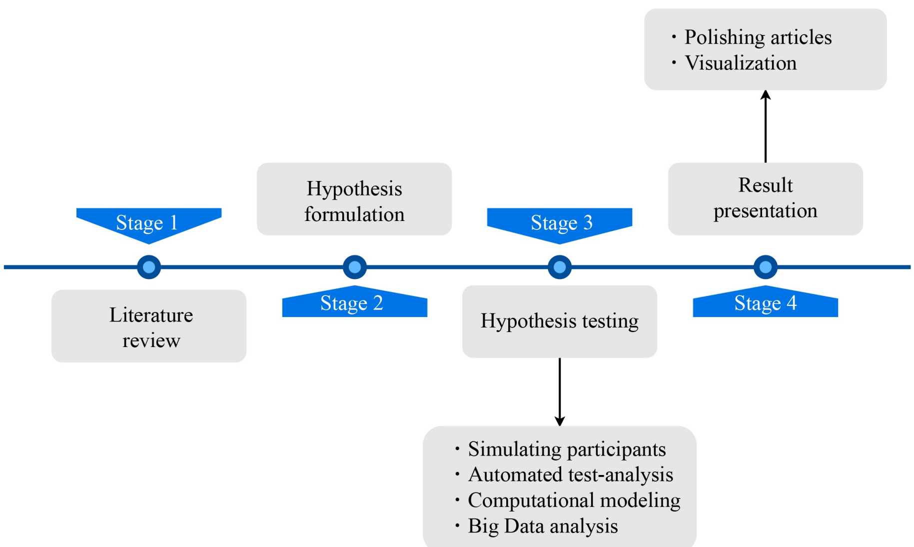

Figure 4 AI applications in traditional psychological research.

keywords. Tools based on natural language processing technology, such as the *Dimensions* platform, can directly transform user queries into relevant literature. Furthermore, researchers can use specific corpus-based fine-tuning or prompt engineering to automate the generation of research hypotheses in psychology (Banker et al., 2024). In the critical hypothesis testing phase, various AI algorithms offer intelligent solutions tailored to different data sources. First, LLMs can simulate human participants in psychological research. For instance, unmodified GPT-3.5 is highly consistent with human moral judgments (Dillion et al., 2023). The online crowdsourcing platform AITurk, built on ChatGPT, can reduce time costs by a factor of 1440 and economic costs by a factor of 30, while maintaining an accuracy of more than 90% (Qin et al., 2024). Second, AI algorithms can help researchers extract valuable information and patterns from vast amounts of text data (Boyd & Schwartz, 2021). For example, the deep learning model BERT can classify and mine emotions embedded in Twitter posts using supervised learning techniques (Chintalapudi et al., 2021); topic modeling algorithms can aggregate semantic information from open-text responses, converting vast, disordered data into foundational themes (Gao et al., 2024). Third, computational modeling methods can refine and analyze complex human social behaviors, ultimately quantifying them into actionable algorithms (e.g., Li et al., 2022). Previous studies have used word embedding techniques to develop models such as the fill-masked association test (Bao, 2024) and word embedding association test (Caliskan et al., 2017) to examine biases, stereotypes, and attitude shifts in human society. Fourth, intelligent algorithms can enhance the efficacy of big data analysis. Current research can use large-scale, diverse data mining to analyze the complexities of human social psychology and behavior (Jackson et al., 2019; Jackson & Medvedev, 2024). Following hypothesis testing, AI can also improve the results presentation phase, boosting researchers' efficiency. Generative AI can assist researchers in academic writing by providing relevant suggestions based on appropriate prompts (Gruda, 2024) while enhancing the data visualization process (Ye et al., 2024).

Based on the above understanding, we suggest augmenting the psychology curriculum with content on AI technologies, including basic programming skills and proficiency in using AI applications. During the literature review phase, we recommend that professional teachers instruct students on the proper use of AI technologies. This approach can help students save time that would otherwise be wasted on aimless searches, promoting the efficient use of AI without encouraging plagiarism or copying. In the hypothesis generation phase, researchers in each subfield can fine-tune open-source LLMs using specialized databases, as needed (such as by summarizing corresponding abstracts or collections of articles), or by designing prompt engineering strategies. During this phase, it is crucial to cultivate students' sensitivity to psychological hypotheses, enabling them to generate reasonable, novel, and meaningful psychological hypotheses independently. In this context, LLMs should be used as auxiliary tools, rather than as a substitute for human thinking. The most critical hypothesis testing phase calls for training in the use of specialized programs, building on the foundation of programming courses, to equip students with the basic principles and skills for using AI in scientific research. On this basis, students should be encouraged to develop the mindset of using AI to solve psychological problems and challenge the limitations of existing technological pathways. Finally, in the results presentation phase, the focus should be on enhancing the readability and aesthetics of the paper through polishing and visualization. Therefore, relevant teaching should emphasize the cultivation of students' skills in using relevant software and web tools.

We believe that teaching AI technologies to psychology students offers several advantages. First, the correct and standardized use of AI can assist psychology students in organizing existing literature, identifying scientific problems, generating hypotheses, designing experiments, collecting and interpreting data, refining manuscripts, and generating visualizations, thereby significantly enhancing research efficiency (Wang et al., 2023). Second, programming, as a mathematical language of communication, embodies the underlying logic and thinking of computational technologies such as AI. If psychology students master basic programming skills, they can not only use them to solve research problems but also gain a more nuanced understanding of the operational logic of computers. This, in turn, can deepen their comprehension of modern cognitive psychology, which is premised on the assumption of "isomorphism between the human brain and the computer" (Simon, 1979). Additionally, even without mastering the mathematical principles of AI, psychology students can still learn to use AI software to address psychological issues. Traditional psychological research methods have long been criticized for challenges such as sample bias ("WEIRD" populations, refer in particular to the western, educated, industrialized, rich and democratic samples), low replicability, and strong situational dependence (Camerer et al., 2018; Henrich et al., 2010). The AI technologies described above can effectively mitigate these risks, providing a more robust methodological foundation for uncovering the objective laws of the psychological world.

"AI of psychology" focuses on treating AI as a research subject, using traditional psychological research paradigms and methods (across various subfields) to explore innovative research themes. Different subfields of psychology address different research themes: Social psychology examines "the other," educational psychology focuses on "learning," developmental psychology on "growth," personality psychology on "traits," clinical psychology on "disorders," and cognitive psychology on "information processing." The expansion of psychological research through the lens of AI is not merely the addition of new objects of study; it actually represents a conceptual shift in research themes. For instance, social psychology has traditionally focused on cognition and behavior in the presence of others. The emergence of AI can be viewed as the introduction of an alternative social agent (Yam et al., 2024). Studies have found that people tend to anthropomorphize AI (Nielsen et al., 2022), and the impact of AI on individuals mirrors this tendency (Qin et al., 2022). However, anthropomorphism implies a "human-like but not human" quality, meaning that AI still differs from humans in some significant ways (Epley et al., 2007). Numerous studies have consistently demonstrated that people are generally averse to AI participating in various social activities (Williams & Lim, 2024). Moreover, in educational psychology, research is focused on whether AI can enhance teaching effectiveness and performance, as well as the potential risks it poses (Lee & Chung, 2024; Yan et al., 2024). Clinical psychologists are exploring whether and how AI can function as a qualified intelligent counselor (Aktan et al., 2022; Yin et al., 2024). Finally, foundational research in personality psychology and cognitive psychology is increasingly concerned with AI—particularly LLMs, examining their stable traits and cognitive task capabilities in order to determine the future development trajectory of AI (Binz & Schulz, 2023; Pellert et al., 2024). To clarify the basic structure of AI of psychology, we categorize the field using a simpler binary structure: static research and dynamic research. Static research involves treating AI as a stationary object, focusing on analyzing its personality, tendencies, and capabilities. Dynamic research, in contrast, examines the bidirectional influence between humans and machines in interactive settings.

Based on the above analysis, we believe that psychology education needs to stay closely aligned with cutting-edge research issues and teach students to identify unexamined scientific questions, rather than merely disseminating classical theories and knowledge. Although the history of psychology is relatively brief, the knowledge recorded in traditional textbooks has already diverged significantly from current research. Upper-year undergraduate and graduate students must master fundamental research skills to develop a psychological perspective that will allow them to critically engage with the world around them. We suggest that educators encourage students to explore AI-related issues across different areas of psychology. In social psychology, we encourage students to identify new AI applications and examine public attitudes toward these technologies, considering the changes AI brings to human society and exploring how humans and AI can collaborate meaningfully and effectively. In clinical psychology, we urge students to develop chatbots capable of supporting psychological counseling and therapy, thereby assisting human counselors and extending help to a greater number of people in need. In cognitive psychology, students should be encouraged to test AI's cognitive abilities using classic cognitive tasks while exploring ways to enhance its similarity to human intelligence. In personality psychology, we recommend that students investigate the distinct styles and perceptual differences exhibited by different AI systems. In developmental psychology, we encourage students to reflect on how the emergence of AI as a societal entity might influence child development, considering whether future generations may experience changes as a result. In summary, we propose that psychology education in the digital intelligence era must incorporate discussions of AI. Students should approach this from the perspectives of various subfields, examining the impact of AI as a new, alternative societal agent on both individuals and communities. Practically, this requires psychology educators to stay informed about the developments in AI and continually explore the potential intersections between AI and their respective areas of research.

4 Conclusion: AI-Driven Psychology Education Revolution

The future is already here. In the era of digital intelligence, psychology education urgently needs a revolution to cultivate future-oriented, adaptable, and interdisciplinary talents. We argue that AI will be the driving force behind this revolution. In this paper, we outline an AI-driven transformation of psychology education, a bold initiative aimed at preparing students for a future where humans and machines coexist. We summarize the crises and challenges that human society faces in the digital intelligence era: the risk of unemployment, unequal resource distribution, the reshaping of human nature, and cognitive distortions. Although AI has led to significant advancements in productivity, the transformation of societal structures may expose us to potential risks of normlessness. In this context, psychology—committed to describing, explaining, predicting, and controlling human psychological and behavioral patterns—must shoulder a critical responsibility: to nurture adaptable and digitally literate talent.

This paper proposes two models to analyze this educational revolution. The first model, aimed at knowledge-oriented foundational education, introduces a teaching loop model that breaks down the psychology education process into five components and explores the possible applications of AI at each stage. This loop model reveals the fundamental principles and processes of learning and provides a framework for understanding the complex and diverse applications of AI in higher education. The second model, designed for research-oriented advanced education, presents the "chimeric research" framework, which organizes the intersection of AI and psychology. The concept of chimeric research includes two main types: AI for psychology and AI of psychology. The former focuses on technology and methodology, aiming to enhance traditional psychological research paradigms with new AI methods. The latter centers on research questions, treating AI as a new object of psychological inquiry and using traditional research paradigms to address contemporary issues.

In summary, this paper proposes a conceptual vision for the reform of psychology education in the digital intelligence era. We introduce a circuit model to explain the application of AI in knowledge teaching and propose a chimeric framework to standardize innovative research. We believe that such an attempt has three comparative advantages: First, guided by the outcomes-based education theory, our clear division of psychology education stages vividly demonstrates the shift in educational focus while reflecting the transformation of psychology talent needs in the digital intelligence era. Traditional teaching theories emphasize the transmission of basic knowledge. However, the rise of AI has compelled contemporary and future students to become problem posers and solvers rather than mere memorizers and knowledge acquirers. Second, the proposed circuit model is based on the self-regulation theory and emphasizes the cultivation and exercise of students' agency. We argue that, in the age of AI, autonomy is not only a basic psychological need of humans but also an essential component of human nature. AI technologies should assist and enhance human agency rather than replacing it. Third, the chimeric research framework provides clear guidance for cultivating research-oriented talents with innovative capabilities. As a pioneering product of new social transformations, AI is bound to change social structures and social cognition. Therefore, it is necessary and urgent to cultivate psychology talents who are adept at using AI technologies to address social issues caused by AI.

Of course, this educational revolution is just beginning. With the continuous progress of AI technology, once artificial general intelligence becomes a reality, society will undergo a complete digital and intelligent transformation. As this occurs, society will require an increasing number of digitally skilled individuals to respond to rapid developments and changes. The educational reform ideas proposed in this paper still require validation through time and practice.

Conflict of Interest The authors declare that they have no conflict of interest.

Data Availability Statements The authors confirm that all data generated or analysed during this study are included in this published article.

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