

# Artificial Intelligence Providing a More Optimized Assessment Tool for Comprehensive Geriatric Assessment

Na Guo, Jian Guo, Xinxin Yan✉

**Abstract:** With the continuous development of science and technology, artificial intelligence (AI) is coming into our lives and changing our lives. Since China entered the aging society in 2000, the degree of population aging has deepened. Comprehensive geriatric assessment (CGA) is now the accepted gold standard for the care of older people in hospitals. However, some problems limit the clinical application, such as complexity and time consuming. Therefore, by analyzing previous studies, we summarize some existing AI tools in order to find a more optimized assessment tool to complete the entire CGA process.

**Keywords:** artificial intelligence (AI); comprehensive geriatric assessment (CGA); wearable devices; deep learning model; image acquisition

## 1 Introduction

Since China entered an aging society in 2000, the degree of population aging has continued to deepen, and it is expected that by 2050, the proportion of people over 65 years will increase to 27.9% [1]. Primary healthcare challenges for the elderly include the management of chronic diseases, physical frailty, and palliative care [2] and the increase in demand for specialized geriatric services (SGS) [3]. Comprehensive geriatric assessment (CGA) is one of the core techniques of modern geriatrics and an effective means of screening for geriatric syndromes [4, 5]. CGA has been applied in various fields of geriatric medicine, such as frailty assessment [6], elderly cancer patient assessment [7, 8], and delirium in

older patients with hip fracture trauma [9–11]. It is a multidisciplinary approach to assess the physical function, psychological and social behavior ability, and environmental health of the elderly to develop treatment plans to maintain and improve the health and functional status of the elderly to maximize quality of life [5, 12, 13]. From the perspective of social health management, China's Ministry of Civil Affairs issued the industry standard for the assessment of the ability of the elderly in 2013 (mz/T 001-2013) [14], which consists of four perspectives: activities of daily living (ADLs) (Tab. 1), mental state, perception and communication, and social participation. In conclusion, CGA improves healthy aging from the prevention perspective and involves many subjects. Unfortunately, there are still some defects in the specific operation process of CGA.

## 2 Defects in CGA of Elderly Adults

### 2.1 An Insufficient Number of Assessors and Significant Differences in Evaluation Levels

In China, assessors may be geriatric nurses or

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**Tab. 1 Activities of daily living (ADLs)**

Activity	Score
Bathing	(1 point) Bathes self completely or needs help in bathing only a single part of the body, such as the back, genital area, or disabled extremity.
	(0 point) Needs help with bathing more than one part of the body, getting in or out of the tub or shower. Requires total bathing.
Dressing	(1 point) Gets clothes from closets and drawers and puts on clothes and outer garments complete with fasteners. May have help tying shoes.
	(0 point) Needs help with dressing self or needs to be completely dressed.
Toileting	(1 point) Goes to toilet, gets on and off, arranges clothes, cleans genital area without help.
	(0 point) Needs help transferring to the toilet and cleaning self or uses bedpan or commode.
Transferring	(1 point) Moves in and out of bed or chair unassisted. Mechanical transferring aides are acceptable.
	(0 point) Needs help in moving from bed to chair or requires a complete transfer.
Continence	(1 point) Exercises complete self-control over urination and defecation.
	(0 point) Is partially or totally incontinent of bowel or bladder.
Feeding	(1 point) Gets food from plate into mouth without help. Preparation of food may be done by another person.
	(0 point) Needs partial or total help with feeding or requires parenteral feeding.
Total points:	-----

Notes: 6 points: High (patient independent); 0 points: Low (patient very dependent).

refresher doctors and graduate students in the teaching hospital. Due to the differences in education and clinical experience in geriatrics, the results of CGA are susceptible to subjective factors. Especially the accuracy of psychological and nutrition assessment is questionable, so the CGA needs multidisciplinary collaboration. However, the number of assessors is seriously inadequate, whether geriatricians or multidisciplinary doctors in the current national situation. In addition, the assessment forms and standards used in the geriatric department of different hospitals are also inconsistent. For example, some medical institutions use the ADL scale and some use the Barthel index assessment scale to assess daily living ability. These will affect the evaluation results and mutual recognition among the different hospitals.

### 2.2 Time-Consuming and Inflexible Assessment Process

It takes more than 40 min for skilled assessors to complete a CGA for the elderly with normal vision, hearing, and comprehension. When the elderly cannot cooperate well, the actual time of CGA is much longer. In addition, it is challenging to combine the self-assessment with the specialist assessment and to complete the entire assessment only in the family, outpatient, com-

munity and other environments. Therefore, the entire assessment process can only be completed during hospitalization, making the assessment inflexible and affecting the medical cost. Fig. 1 is a flowchart of CGA for a patient after admission. The CGA includes five parts: physical, functional, psychological, social and environmental. And according to the results of CGA, doctors make the next diagnosis and treatment plan. CGA=Comprehensive geriatric assessment; ADL=Activities of daily living; GAD-7=Generalized anxiety disorder 7-item; PHQ-9=Patient health questionnaire 9-item; OSTA=Osteoporosis self-assessment tool for Asians; NRS 2002=Nutritional risk screening 2002; MMSE=Mini-mental state examination; PSQI = Pittsburgh sleep quality index; SPPB = Short physical performance battery.

### 2.3 Post-Assessment Follow-up and Clinical Data Collection

Some medical institutions have developed an electronic information-based online CGA entry system, which requires medical personnel to complete online assessment forms through online operation, then automatically generate the paper version of the evaluation report, and export excel table data. However, there are some problems in clinical applications, such as the purchase of electronic bedside equipment, the mastery of the



computers, computational intelligence is superior to the human brain in many fields, such as search and precision marketing. Perceptual intelligence is the simulation of human cognitive ability through mathematical modeling and extensive data learning, such as speech recognition, image recognition, etc. Cognitive intelligence is the simulation of human reasoning, ideals, and knowledge organization capabilities, such as IBM's Watson [17], a technology platform based on big data and machine learning. In health care, there are three products: Merge Healthcare, Phytel, and Truven Health Analytics. Merge Healthcare can analyze x-rays and magnetic resonance imaging (MRIs). Phytel can help patients communicate. Truven Health Analytics can analyze complex medical data. Despite IBM's investment, Watson Health has had success in fields such as oncology and genomics, but the disappointing result is that Watson Health has not triumphed in the medical field. In July 2018, Watson was found to have a fatal bug, prescribing bleeding-prone drugs to cancer patients with bleeding symptoms that could lead to death. In April 2019, IBM announced that the AI-based drug discovery program had stopped reaching new customers due to poor market performance. Watson was once considered a "Joke, Hoax and Quack". IBM Watson's product is unlike the "Super Doctor" one once envisioned. And more doctors complained: "We bought Watson because it was so well marketed that we thought we could use it to achieve some vision. But it can do nothing!" It suggests that the rapid development of AI cannot yet replace the core technology of medicine. These tools are expected to change the status of geriatric assessment by providing the means of acquiring, storing and analyzing multifactorial complex aged assessment data, while capturing its nonlinear dynamic variability and providing the valuable data of predictive analysis. In this way, overcoming the inadequacies of traditional statistical methods, AI can handle large volumes of data with high heterogeneity and complexity generated by instrumented geriatric assessment

and simplify the assessment process. It may be a promising solution.

## 4 Artificial Intelligence and Comprehensive Geriatric Assessment

In the field of CGA, Wei-min Chu et al. [18] used AI technology to predict the incidence of falls in elderly patients. The study included 1101 elderly patients hospitalized in a single medical center in central Taiwan between 2018 and 2019. The 21 physiological and clinical data from their electronic health records (EHR) with their CGA were collected, including demographic information, vital signs, visual ability, hearing ability, previous medication, and activity of daily living. They separated the data into 3 datasets and applied 6 models. The models not only includes conventional machine learning models such as Extreme Gradient Boosting (XGBoost), light Gradient Boosting Machine (LightGBM), Random Forest and logistic regression, but also deep learning models such as deep neural network (DNN). Finally, they found that the machine learning algorithms XGBoost (73.2% accuracy), LightGBM, Random forest, SGD, and logistic regression were successfully trained. In geriatric medicine, this study was the first study based on machine learning using both EHR and CGA to predict the risks of falls in the elderly. Raquel Fuentetaja [19] believed that the CGA consists of four dimensions, including physical function, cognitive function, social capacity, and environmental health. Firstly, patients and their families conduct clinical interviews to understand the situation. Secondly, doctors assess the function, and cognitive, motor, and social relationships of patients through multidimensional evaluation. Finally, the doctors collect the results of the first two steps and develop an individualized care plan. In an attempt to automatize the procedure and save clinicians' time to concentrate on more added-value tasks, the European Project ECHORD++ (see <http://echord.eu> for more information.) launched a robotics challenge

named CLARC in 2015 to perform phase 2 of CGA [20]. The robot helps doctors collect information and should autonomously perform tests while doctors discuss with their relatives. It may reduce the duration of the CGA process, avoid waiting time for patients and their families, and save clinicians' time. However, it is only in hospitals. Additionally, there are several AI technologies that could have potential applications in CGA.

#### 4.1 Assessment of Physical Function

Some small and convenient gait devices have been used to assess gait and balance function in patients, such as pressure pads, pressure insoles, motion capture systems, and healthcare wearable devices (HWDs), which are used primarily to assess gait damage in patients with cerebrovascular disease [21]. 1) The main principle of pressure pads is that the sensor is integrated into a special pad. When patients walk on the mat, pressure data is measured and collected so that space-time parameters such as gait speed, step length, and step width can be determined. However, the pads must be mounted on the ground for testing, need a specific functional space, and be costly and nonportable. And it cannot collect information on body posture or joint kinematics. 2) The pressure insole is used to place the pressure measuring device in the shoes. It is more convenient and economical, but the measuring accuracy is lower. 3) The motion capture system, which is a tag-based optical capture system, can obtain joint motion angles and angular velocities in the sagittal plane, frontal plane, cross-sectional plane, and space-time parameters such as walking speed, step frequency, and step length through the computer-aided joint kinematics and dynamics measurement system of the numerical calculation. However, due to soft tissue artifacts, the location of the marker on the skin surface, and other factors, may lead to a decrease in the accuracy of the measurement. 4) Healthcare wearable devices (HWDs), which can monitor blood pressure, electrocardiogram, pulse, blood

oxygen, body temperature, respiration, electroencephalogram, and electromyography, are sensors and transducers to convert human or environmental signals into valuable data. There are different ways to wear HWDs: contact wearable device, implanted wearable device, and wearable sensor with additional device [22, 23]. The Chinese Academy of Sciences has developed a portable wearable gait analysis system, Gaitbot, which makes a hardware board based on a microphone transducer fixed to an acrylic rectangle using a 3D printer and an elastic band to secure the ankle. The microphone sensor can pick up gait information directly from footsteps as the wearer moves between the foot and the floor [24]. Previous studies have demonstrated that a gaitbot is an ideal system for identifying abnormal gait in patients with type 2 diabetes [25]. In addition, new sensors have been developed to monitor blood glucose in real-time in diabetic patients, such as noninvasive blood glucose detection devices [26]. The Apple Watch Series 8 has a built-in health sensor that can not only record people's heart rate, blood oxygen, medication records, fall monitoring, and sleep duration but also record the time people are awake, awake, rapid eye movement sleep (REM), core sleep or deep sleep. The Apple Watch Ultra is also equipped with running form measurements that can measure stride length, touchdown time, and vertical amplitude to aid in running efficiency [27, 28] (Fig. 2). The advantages of HWDs are convenient, intelligent, dynamic, and real-time. It provides essential data for the management of chronic disease, personalized medicine, and telemedicine. The synthetic multiparameter combination model can be used to evaluate several clinical indexes simultaneously. As a result, wearable devices are the most promising AI technology for CGA to assess not only gait and dynamic blood glucose, but also heart rate variability, sleep efficiency [29], drug concentration [30], etc. However, so far, the wearable is still developing, the CGA for the elderly. There is a long way to go to popularize clinical geriatrics.



Fig. 2 The Apple Watch

### 4.2 Assessment of Cognitive Skills

The Mini-Mental State Examination (MMSE) [31] (Tab. 2) was usually used to assess the cognitive abilities in CGA, including closed- and open-answer questions, which poses more challenges from the view of AI. In the study of Alzheimer’s disease (AD), many researchers have found that the clinical assistant diagnosis system of AD is based on deep learning. First, the system uses the MRI image presentation text report of AD patients in a top three hospital as training data through a combination of Hierarchical Bidirectional Long Short-Term Memory (hierar-

chical BI-LSTM) and Attention Mechanism Attention, which was constructed to achieve a clinical classification diagnosis of AD. Second, using data from the Alzheimer’s Disease Neuroimaging Initiative (ADNI), data from at least three times AD clinical examinations in a year were entered into the system, including basic information such as age, sex, education level, genetic information, and neuropsychological assessment of the patient. The model was constructed using the combined Attention mechanism BI-LSTM to predict disease progression after one year. This system not only proposes the AD diag-

Tab. 2 Mini-mental state examination (MMSE)

Domain	Maximum score
<b>Orientation</b>	
What is the (year) (season) (date) (day) (month)?	5
Where are we: (state) (country) (town) (hospital) (floor)?	5
<b>Registration</b>	
Name 3 objects: I second to say each. Then ask the patient all 3 after you have said them. Give 1 point for each correct answer. Then repeat them until he learns all 3. Count trials and record.	3
<b>Attention and Calculation</b>	
Serial 7’s. 1 point for each correct. Stop after 5 answers. Alternatively spell “ world” backwards.	5
<b>Recall</b>	
Ask for the 3 objects repeated above. Give 1 point for each correct.	3
<b>Language</b>	
Name a pencil, and watch (2 points)	2
Repeat the following “No ifs, ands or butts” (1 point)	1
Follow a 3-stage command: “Take a paper in your right hand, fold it in half, and put it on the floor” (3 points)	3
Read and obey the following: Close your eyes (1 point)	1
Write a sentence (1 point)	1
Copy design (1 point)	1
	1
<b>Total score</b>	-----

Notes: The MMSE evaluates 6 cognitive domains, i.e., memory, orientation, registration, attention, language, and visuoconstruction ability. It has a maximum score of 30 and a recommended cutoff score of <24 for dementia.

nosis classification model, but also suggests the disease development prediction model [32].

Deep learning is a part of AI that is equivalent to the perceptual intelligence stage of AI. Their relationship is like being concentric circles, the idea that came first, then machine learning, and finally deep learning, which is driving today's AI explosion (Fig. 3). It simulates human perception ability through mathematical modeling and significant data learning. In the specific operation process, it is divided into the patient-side and the doctor-side: the patient-side needs to upload basic information, disease, symptoms, and cranial MRI data. The doctor can consult the AI diagnosis system to give the final diagnosis opinion and make the treatment plan. The accuracy and model stability of deep learning is proved to

be better than those of conventional inspection techniques. Deep learning model analyzes the diagnosis of AD from two perspectives of patients and doctors. AI diagnosis system can give the diagnosis opinion and make the treatment plan (Fig. 4).

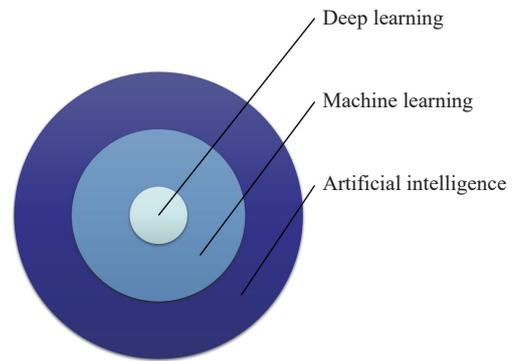


Fig. 3 Artificial intelligence

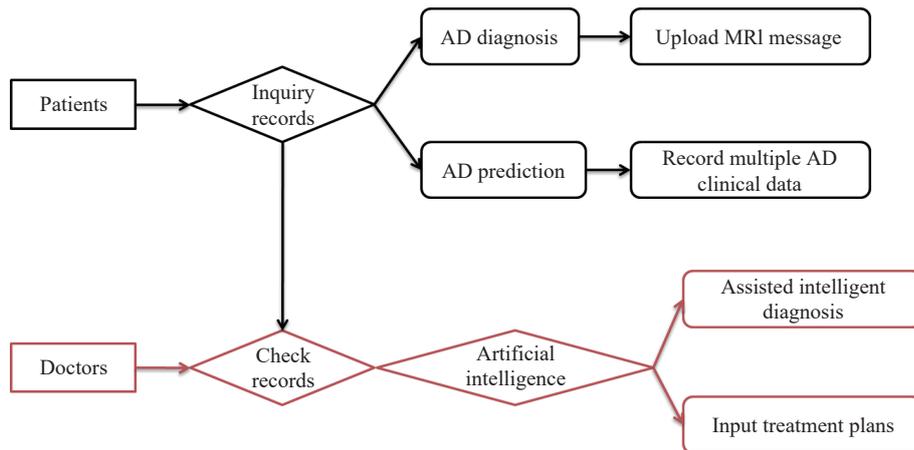


Fig. 4 Deep learning model

### 4.3 Assessment of Psychological

Recently, more than 10 000 mental health applications have been available to consumers, and are increasing daily. However, some studies suggest that most mental health Apps on commercial marketplaces do not conform to clinical guidelines [33]. Therefore, there is still much to explore in the field of psychological assessment. Nicholas et al. used machine learning models that predicts the prognosis of treatment for changes in anxiety and depressive symptoms and may be used to guide future decision-making between low-resource digital interventions or higher levels

of traditional care [34]. Marta R et al. constructed a set of artificial neural networks (ANNs) to analyze data, learn from them, and then make classifications, diagnoses, or predictions [35]. ANNs are used when there is a need for complex answers and algorithms, and possible relations between the data are unknown. There is a wide range of functionalities provided by these algorithms, which makes them promising for use in predicting of psychology, including mental health, behavior, emotions, and personality traits [36, 37]. And approaches explicitly concentrates on statistical learning of nonlinear func-

tions from multidimensional data sets to make further generalized predictions about data vectors that will not be seen during training. Thus, they can potentially boost decisions associated with diagnosis, prognosis, and treatment in psychology and psychiatry [38]. Implementations ANNs could help psychology become a more predictive science that can induce a better understanding of human behavior [39]. Matthew D et al. used a novel machine learning pipeline to re-analyze data from an observational study to predict generalized anxiety disorder (GAD) and major depressive disorder (MDD). The channel constitutes an ensemble of algorithmically distinct machine learning methods, including deep learning. A sample of more than 4 000 undergraduate students completed the study, undergoing a general health screening and completing a psychiatric assessment for MDD and GAD. The performance of the model in a held-out test set found an AUC of 0.73 (sensitivity: 0.66, specificity: 0.7) and 0.67 (sensitivity: 0.55, specificity: 0.7) for GAD and MDD, respectively. But the limitation is that the initial screening for the outcomes of MDD and GAD may not have captured all cases within the population. The data set comes from students of French university, not from the elderly [40]. ANN is an early form of deep learning, however people don't use it anymore in recent years. In summarize, AI-related cognitive assessment needs further study in elderly adults.

#### 4.4 Assessment of Social Capacity and Environmental Health

We can master more clinical data from patients by machine learning based computer vision techniques. In J Yang's study, AI technology was more accurate than human experts in detecting scoliosis through computer-based deep learning of back images and algorithm innovation. This method only requires one picture of the naked back, which is convenient and rapid, and it is beneficial for large-scale scoliosis screening [41]. With the improvement of computer algorithms,

big data and camera accuracy, video grating technology can be applied to surface topography measurement, known as "Diers Formetric 4D". There are several studies on scoliosis that combine computer processing with improving the accuracy and automation of surface topography measurements. In addition, in orthopedic research, 2D CT data can be input into 3D reconstruction software. The image is restored in three planes: coronal plane, sagittal plane, and axial plane, and the measurement of the anteversion angle of the femoral neck was made [42]. We hypothesized that AI can process videos and images of patients' daily life to assess their ability an environmental health, not limited to specific scales, such as Barthel's index rating scale [43]. Therefore, the assessment of the daily life of the elderly through AI technology leads to more objective conclusions, reduces subjective interference, and makes home self-test possible.

## 5 Problems

As the development of science and technology, AI is continuing to penetrate all aspects of our lives, however there are still problems in elderly CGA.

- 1) The elderly are in a weak position in society. Their physical strength, vision and hearing have declined. The speed of solving problems and dealing with problems is slow. Some people are economically disadvantaged. For example, they cannot afford AI products like the Apple Watch. So AI products should be considered some unique features, such as sound size, speed, definition and price.

- 2) The Internet and extensive data links can bring information security and privacy protection issues, so we need to fully seek the consent of the patient's family in the process of AI participating in the CGA of the elderly, to develop standardized standards. For example, we can require the necessary elements of the scene to be shot, the clarity of the recording equipment,

character dress, and standardized prompts.

3) We still need extensive clinical trials to explore the safety, effectiveness and convenience of artificial intelligence in elderly CGA to realize rapid collection, analysis, and processing of patient disease information and assist decision making. We try our best to provide the individual diagnosis and treatment plan, and at the same time, we should take into account the human culture emotional expression and the teaching goal.

4) An excellent clinical tool must be based on clinical needs-oriented, combined with clinical characteristics, according to clinical goals to develop a plan and ultimately return to clinical. But it is challenging to develop and apply software alone without a clinical background in computer science. So we must seek multidisciplinary cooperation, not just inside the medicine field.

## 6 Conclusion

To sum up, with the rapid development of technologies such as cloud computing, big data and bio-sensing, we boldly envision that in the near future, wearable devices, image acquisition, and deep learning modules will be integrated to provide an economical, fast, and reusable assessment system for the elderly, enabling the elderly at home, in the community, in nursing homes, or in outpatient clinics to enjoy the benefits of CGA. One day, we will make CGA as convenient and rapid as blood pressure measurements and electrocardiograms. It can also increase the follow-up rate, compare before and after treatment, and arrange the outpatient follow-up visit through background management to collect patient condition change data in time. In the community, AI assessment tools are also conducive to long-term exemplary management of chronic disease patients. They will serve a larger population to achieve the objective of accurate diagnosis and treatment and individualized management.

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