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Research article

Life cycle, education, and statistical cognitive ability

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A B S T R A C T

High statistical cognitive ability is an essential factor to achieve high-quality development in the era of artificial intelligence and big data. In this research, we use the machine learning local weighted regression algorithm to analyze the change curve of Chinese statistical cognitive ability throughout the life cycle, as well as the impact of individual education and parental education on statistical cognitive ability of 26,000 individuals from different groups of gender, age, educational background, and family background. All the data analyzed is from the China Family Panel Studies (CFPS). We find that the statistical cognitive ability curve is inverted U-shaped throughout the life cycle, and the years of education, parental education and individual are proportional to statistical cognitive ability. *Keywords:* statistical cognitive ability, machine learning, robust locally weighted and smoothing scatterplots, education, life cycle.

1. Introduction

1.1. Research background

Cognitive ability refers to the ability to receive, process, store and apply information, including verbal cognitive ability, quantitative cognitive ability, and non-verbal cognitive ability. Statistical cognitive ability refers to the ability to process and apply statistical data, draw conclusions, and make decisions from statistical data. In the abstract sense, all sciences are mathematics; based on rationality, all judgments are statistics [1]. Cognitive ability is the foundation of human capital, and statistical cognitive ability is a necessary ability in the era of artificial intelligence [2]. Many of the technologies and systems of AI are highly depended on statistics, for example machine learning system, backpropagation technology, and broad learning system are highly related to statistics [3,4]. In today's world, the data science often represents the function of AI, and the data science or Big Data is built on the function of statistics [5]. The statistical cognitive ability of human capital, therefore, is an essential factor affecting the progress of Al and Big Data. Also, it is necessary to explore the influencing factors of the statistical cognitive ability.

However, the existing literature about cognitive ability cannot directly reflect the influencing factors of statistical cognitive ability since statistical cognitive ability is one aspect of cognitive ability. To explore the influencing factors of statistical cognitive ability, we focus more on factors that can reflect the ability of statistical cognition. Also, most of the existing research applies parametric regression to study the influence of various factors on cognitive ability, but the variables of cognitive ability are not normally distributed, parameter estimation is usually biased. Therefore, nonparametric estimation is more reliable.

1.2. Research significance and limitations

In this study, we use the machine learning locally weighted regression to obtain the statistical cognitive ability curve of each

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influencing factor. The method we use can avoid over-fitting or underfitting of parameter estimation, which more accurately reflects the true correlation of the data. To test the robustness of the method we use, we take age, individual educational background, parental education background, and gender into consideration, which can reflect the statistical cognitive ability of Chinese people more accurate and test the rationality of our research method. The research results can help people plan their study and life more effectively. At the same time, our research findings have very important reference significance for the field of education, especially the field of mathematics education and the field of medicine.

On the other hand, our article also has two limitations. First, the reasons for statistical cognitive decline after age 31 need to be explored in more depth. This requires further research on the integration of multiple influencing factors. Second, our research is mainly aimed at the statistical cognitive ability of Chinese people. Due to the availability of data, we did not conduct analysis and comparison on data from other countries. These two limitations also provide ideas for future research directions. First, interdisciplinary research can be conducted on the disciplines of education, statistics, medicine, and sociology to explore the main influencing factors of the decline in statistical cognitive ability; second, to find the general laws of statistical cognitive ability, a future research need to be conducted to analyze the factors affecting statistical cognition ability from various aspects such as economic development level and education system in different countries to explore the distribution of statistical cognitive ability curves. In addition, we find gender is a factor affecting people's statistical cognitive ability. Our finding seems to confirm the "stereotype" of gender in mathematical skills. However, we find that before the age of 23, women outperform men in statistical cognitive ability. A further study is also suggested to conducted to figure out the reasons.

Meanwhile, our findings could also contribute to the area of technology development. Statistical cognitive ability is an important accelerator of human capital that can improve innovation. In other words, the statistical cognitive ability can reflect the process of the knowledge-based economic development by side. From this point, we also expect future study that can incorporate statistical cognitive ability and knowledge-based economic development.

2. Literature review

Statistical cognitive ability is an important part of human capital, we can see relevant research focuses on the formation of statistical cognitive ability and the affecting factors. The absorptive capacity theory argues that the absorption of new knowledge by an organization or individual can make it more innovative and flexible, with higher levels of performance and competitiveness [6]. But the premise is that organizations and individuals must have a knowledge base to absorb and apply new knowledge, otherwise new knowledge acquired in whatever way or at what cost may not be digested nor absorbed. Knowledge-based theory argues that the way an organization or individual stores and uses internal knowledge, competencies, and talents determines its survival, development, and success [7]. All human productivity depends on knowledge, and all technologies are the concrete embodiment of knowledge, and knowledge is the source of innovation. Social organizations or individuals who are good at searching, absorbing, and utilizing new knowledge from inside and outside will achieve higher performance.

Factors affecting statistical cognitive ability include age, education, parental education, etc. Li and Luo argue that poverty makes children's cognitive ability significantly lower than that of children of the same age by more than 2% [8]. Cognitive achievement has a negative impact, which is magnified by increasing class and school sizes in the promotion of compulsory education [9]. Parents' educational expectations have a significant positive impact on rural children's cognitive ability [10]. Retirement can suppress cognitive decline in the short term, but it has a negative impact on cognition in the long run [11]. The more negative experiences in the early-life growth environment, the worse the cognitive function of the middle-aged and the elderly; and there are certain differences in the effects of different types of negative experiences on the cognitive function of the middle-aged and the elderly [12]. Retirement not only causes the decline of personal cognitive ability, but also has a negative direct spillover effect on the spouse's cognitive ability and has a negative indirect spillover effect through the social interaction of husband and wife [13].

Regarding the measurement of cognitive ability, the Seattle Longitudinal Study (SEAT) measured and analyzed the cross-sectional data of age differences and cognitive changes [14]. Le et al. draws on the design of the SEAT longitudinal research model to test whether the age difference of basic cognitive ability of Chinese adults is consistent with the age difference of basic cognitive ability of American adults [15]. The sample included 120 residents aged 20 to 80 in Tianjin, China. The study found that in the 20–50 age group, the statistical cognitive ability of the Chinese sample was higher than that of the American sample, and the statistical cognitive ability of the Chinese sample decreased significantly in the 50–70 age group, but the American sample remained basically unchanged. To further the research of the statistical cognitive ability, in this research, we use the data of the China Family Panel Studies (CFPS) . CFPS has been investigating cognitive ability, especially statistical cognitive ability since 2010. The sample size is 26,000. The sample we use covers all essential features of the variables explored in this research and is rigorously classified by age, gender, educational background, and family background, which can better represent the whole population of China.

3. Theoretical framework and research methodology

3.1. Research hypotheses

Statistical cognitive ability is the bridge connecting knowledge to technology. Improving people's statistical cognitive ability and maintaining a high level throughout the life cycle are the basic requirements for the whole society to achieve high-quality economic growth in the era of big data. Cognitive ability is divided into verbal ability and rapid learning ability. Rapid learning ability (including statistical cognitive ability) will decline to a greater extent with age [16]. This leads to our research hypothesis 1.

Research Hypothesis 1: Statistical cognitive ability exhibits an inverted U-shaped curve throughout the lifespan.

Many factors affect the development of statistical cognitive ability, and maintaining a high level of social activity, physical exercise, and intellectual activity in daily life can maintain cognitive levels or slow down its decline [17]. The more educated control group was better at slowing down the cognitive decline than the less educated control group [18]. This leads to our research hypothesis 2.

Research hypothesis 2: Individual and parental education level is positively correlated with individual statistical cognitive ability.

3.2. Data description

The data we use in this study comes from CFPS. CFPS is a national and comprehensive social tracking survey project, which reflects China's economic, demographic, educational, and health changes. CFPS focuses on the economic and non-economic well-being of Chinese residents, covering a variety of research topics such as economic activity, educational attainment, family relationships and family dynamics, population migration, and physical and mental health. In 2010, CFPS implemented a baseline survey in 25 provinces, cities, and autonomous regions across the country, and finally completed interviews with 14,960 households and 42,590 individuals. All participants and their future children were defined as the CFPS gene members, who were permanently tracked by CFPS every two years.

The cognitive test of CFPS consists of two sets of questions: the literacy test and the mathematics test. Mathematics is the foundation of statistics, and statistics is the application of mathematics in social practice. Therefore, we use the mathematical test scores of CFPS to represent statistical cognitive ability. The non-parametric regression numerical solutions of age, education, parental education level, etc. On statistical cognitive ability are obtained by using the machine learning locally weighted regression algorithm. Compared with the existing literature, the machine learning nonparametric regression methods have statistically better predictive ability for non-normal statistical cognitive ability.

Research variables include math test scores (mathtest18), math test scores, age (age), years of education (cfps2018eduy), and parental education level (averageedu). To better consist with normal distribution, we use natural logarithm of math test scores (lnmath) instead of the math test scores. Therefore, the result can reflect the correlation more accurately. The descriptive statistics are shown in Table 1.

The sample size of the mathematics test score survey was 26,000, with an average test score of 9.34 points, a minimum of 0 points, and a maximum of 24 points. The normality test results of the math test score, and their logarithms are shown in Table 1. Since the p-values of the skewness coefficient test and the kurtosis coefficient test are zero, the null hypothesis of normal distribution is rejected. Mathematical transformations such as square root, square, and cubic are shown in Fig. 1, however, normal distribution still cannot be obtained. To avoid biased estimation, we use nonparametric regression to analyze the correlation between statistical cognitive ability and variables such as age, years of education, and parents' educational level.

The linear correlation analysis of the variables is shown in Table 2. It can be seen from Table 2 that the math test scores are proportional to the years of education and parental education level and are inversely proportional to age. Due to the non-normal distribution of mathematics test scores, the linear correlation coefficients may be biased and underfitting.

3.3. Estimated research method

Linear regression is a linear method to fit the trend of the data. However, for data with unknown distribution, it cannot be simply fitted in a linear way, otherwise the model will have a large deviation, which violates the basic assumption of statistical unbiasedness, and over-fitting or under-fitting occurs. For parameter estimation whose population does not obey the normal distribution, non-parametric estimation methods are usually used. Non-parametric estimation methods do not make any assumptions about the distribution of variables, and the results are more robust and more realistic. On the other hand, the locally weighted regression (lowess) can better deal with this problem and make better predictions [19]. Therefore, we use locally weighted linear regression in this study and the nonparametric regression model is assumed to be:

$$Y_i = m(x_i) + \varepsilon_i \ , \ \varepsilon_i \backsim \mathrm{iid}\left(0,\sigma_\varepsilon^2\right) \tag{1}$$

In this model, m(x) is unknown in the whole data set, but m (x_i) is a linear equation in the neighborhood u (x_i) with radius h of x_i, then the weighted least square method is used in this neighborhood. The objective function is as below:

Table 1
Variable descriptive statistics.

Variable	Sample Size	Means	Standard deviation	Minimum value	Maximum Value	p Value of Skewness Coefficient	p Value of Kurtosis Coefficient
mathtest18	25972	9.34	6.04	0	24	0.00	0.00
lnmath	23415	2.15	0.68	0	3.18	0.00	0.00
averageedu	29892	2.45	1.16	0	7	–	–
age	37352	44.79	19.37	9	102	–	–
cfps2018eduy	32814	7.74	4.83	0	23	–	–

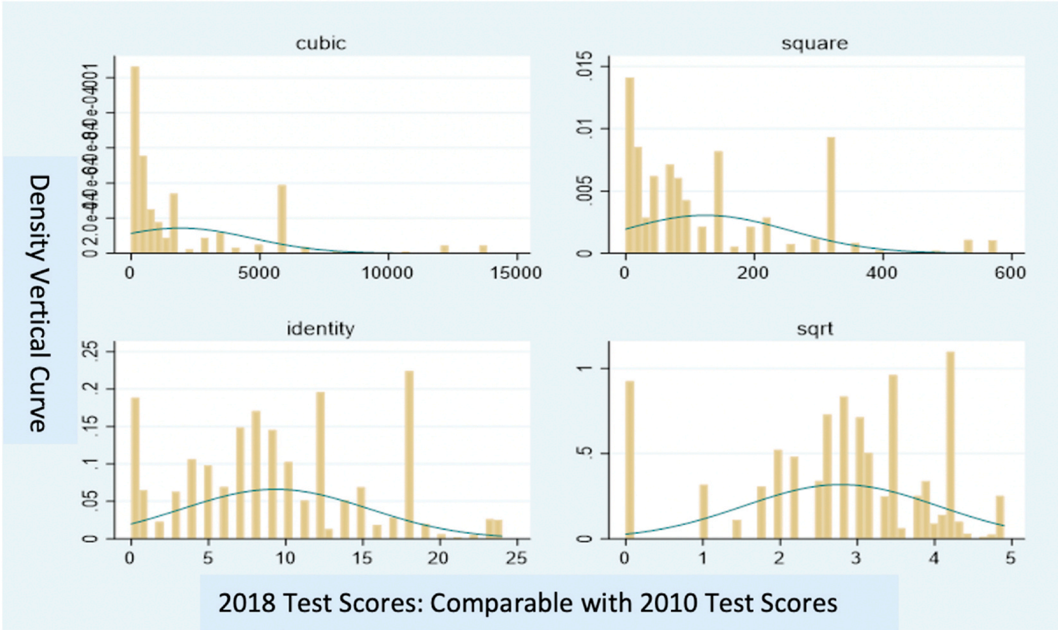

Fig. 1. Test results algebraic transformation results.

Table 2
Variable correlation analysis.

	mathtest18	lnmath	cfps2018eduy	averageedu	age
mathtest18	1				
lnmath	0.91*	1			
cfps2018eduy	0.77*	0.69*	1		
averageedu	0.41*	0.35*	0.30*	1	
age	−0.55*	−0.48*	−0.40*	−0.36*	1

Note: * represents p = 0.05.

$$\min_{x_i \in u(x_0)} \sum k((x_i - x_0) / \mathrm{h})(y_i - \mathrm{m}(x_i))^2 \tag{2}$$

In Equation (2), k (·) is a tricubic kernel function. The neighborhood radius h is the bandwidth, and the locally weighted linear regression uses the optimal bandwidth, so that the prediction of Equation (1) is the best. Use the cross-validation algorithm to find the optimal bandwidth h, so that h satisfies the following objective function:

$$\min_h cv(h) = \sum_{i=1}^{n} (y_i - \widehat{m}_{-1}(x_i))^2 \pi(x_i) \tag{3}$$

In Equation (3), $\widehat{m}_{-1}(x_i) = \sum_{j \neq i} \omega_{jh} y_j$, ω_{jh} is the weight function, which is the estimator of m (x_i) minus the observed value x_i.

$$\pi(x_i) = \begin{cases} 1, 5th\ percentile < x_i < 75th\ percentile \\ 0, others \end{cases} \tag{4}$$

Estimate m (x_i) for each point of the data set separately to obtain the numerical estimation of m(x). Although the analytical solution cannot be obtained, the numerical solution more robustly reflects the real correlation between variables. Through cross-validation across the entire dataset, y = m(x) reflects a more realistic and reliable correlation between variables.

4. Regression result and robustness test

Locally weighted regression is a nonparametric statistical method for fitting scattered data to obtain a smooth curve and a powerful tool for analyzing two-dimensional variables. It takes a sample point as the center, intercepts a set of data with a length of h forward and backward, performs a weighted linear regression for this set of data, and makes a weighted regression line for all data points, and the line connecting the center values of each regression line is the Lowess curve of the data. Using the locally weighted regression model (1), where the dependent variable is the math test score and the independent variable is age, the numerical solution of the locally weighted regression can be obtained, as shown in Fig. 2.

It can be seen from Fig. 2 that from 9 to 20 years old, statistical cognitive ability increases rapidly; from 21 to 30 years old, statistical cognitive ability maintains the highest level; after 31 years old, statistical cognitive ability begins to decline; before 45 years old, statistical cognitive ability is above the average level throughout the lifespan; and after 46 years old, statistical cognitive ability falls below the average level.

4.1. Statistical Cognitive Ability and Years of Education

The data from CFPS database in 2010 and 2014 also proves that the statistical cognitive ability curve is unimodal rather than multimodal, with the highest peak across the lifespan between the ages of 9 and 30. The decline of statistical cognitive ability after the age of 31 cannot be reversed. Also using model (1), the dependent variable is math test scores, and the independent variable is years of education, and a partial weighted regression graph can be obtained, as shown in Fig. 3.

In the sample, the minimum education period is 0 year, and the maximum education period is 23 years. Years of education were highly positively correlated with statistical cognitive ability. Access to higher education is an effective approach of improving statistical cognitive abilities, and education is an endogenous factor that can be achieved through individual effort. By receiving more education and improving the peak of personal statistical cognitive ability, people can improve their judgment ability and delay the decline of cognitive ability.

From Fig. 4, we can see that throughout the life cycle, the statistical cognitive ability of the population with a college degree or above is significantly higher than that of other populations, and the statistical cognitive ability reaches peak at the age of 25, and the statistical cognitive ability of the elderly over the age of 60 remains above 5 points. In the whole life cycle, the statistical cognitive ability of the population without college degree is significantly lower than that of the population with college degree, and the gap is even more obvious after the age of 60.

4.2. Statistical Cognitive Ability and Parents' education level

Using model (1) as above, we can see from Fig. 5 that parental education is positively correlated with children's statistical cognitive ability, but there is a phenomenon of obvious diminishing marginal returns. The correlation coefficient of parents with college degree or above on children's statistical cognitive ability is much smaller than that of parents with high school education and below.

4.3. Statistical cognitive ability and gender

Using model (1), math test scores are used as the dependent variable, age is used as the independent variable, and partial weighted regression is performed according to gender. The numerical solution curve is shown in Fig. 6. The statistical cognitive ability of women is higher than that of men before the age of 22, and the statistical cognitive ability of men is higher than that of women and the rate of decline is lower than that of women in the life cycle after the age of 23. The older the age, the more obvious the difference is.

From the partial weighted regression results, we can tell that age is negatively correlated with individual statistical cognitive ability, and individual years of education, parental education level and individual statistical cognitive ability are positively correlated. To verify the robustness of the results and improve the estimation efficiency, half Parametric model and linear regression model are used for parameter estimation. The dependent variable is the math test score, the independent variables are the years of education, the average educational level of parents, and the nonparametric part of the function m(x), where x is the age of the sample. The regression

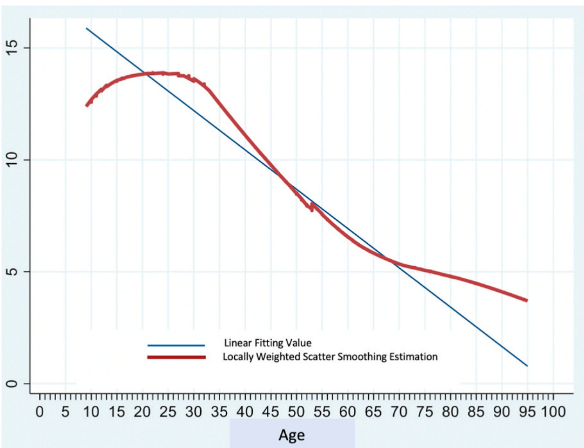

Fig. 2. 2018 statistical cognitive ability and age.

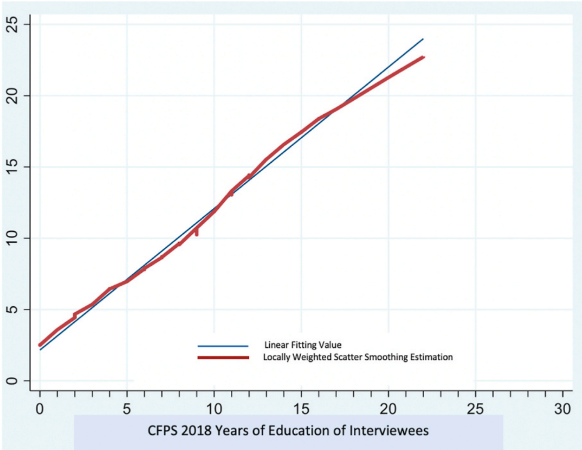

Fig. 3. Statistical cognitive ability and years of education.

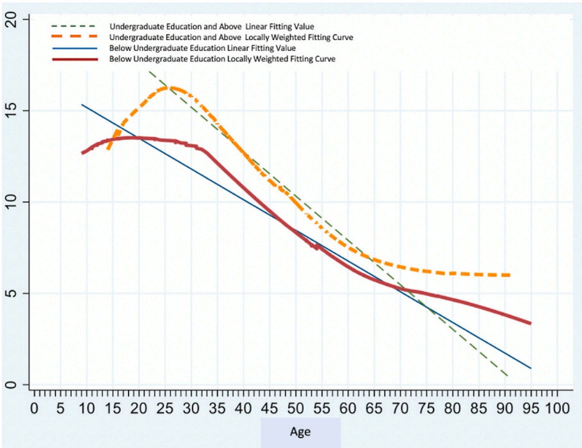

Fig. 4. Statistical cognitive ability and level of education.

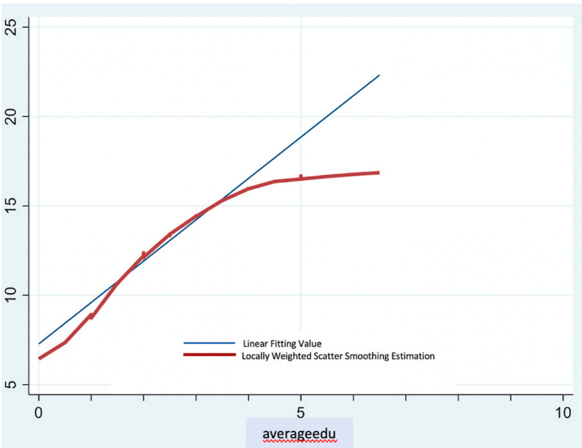

Fig. 5. Children's statistical cognitive ability and parents' level of education.

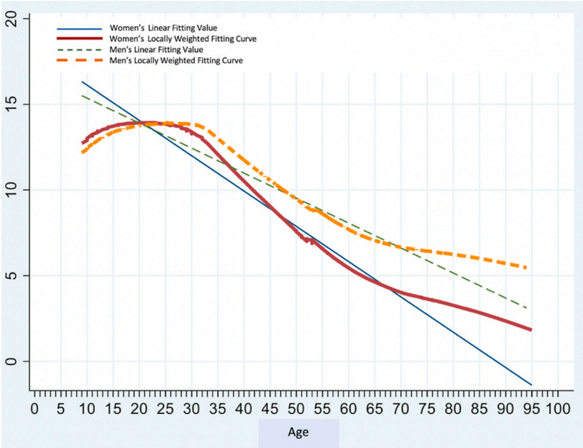

Fig. 6. Children's statistical cognitive ability and parents' level of education (gender).

results are shown in the table attached.

From the regression results in Table 3, we can see that statistical cognitive ability is positively correlated with the educational level of parents and the educational level of the respondents, and negatively correlated with age. Whether it is semiparametric regression or linear regression, the coefficient signs are the same, so the results of nonparametric regression are robust.

5. Discussion and conclusion

We study the influence of life cycle, years of education, and parental education on individual statistical cognitive ability, and find the numerical solution. Using a machine learning locally weighted regression algorithm, a statistical cognitive ability curve was fitted. We find that.

(1) Recall the study of Li and Luo [2], our finding confirms that age is an important factor affect people's cognitive ability. The reason of the decline of cognitive ability could be strongly related to the change of environment or the degeneration of health [20]. The curve of statistical cognitive ability showed an inverted U-shaped unimodal curve. After the age of 31, the statistical cognitive ability generally showed a downward trend with the increase of age. From 9 to 20 years old, statistical cognitive ability increases rapidly; from 21 to 30 years old, it remains at the highest level; after 31 years old, statistical cognitive ability begins to decline; before 45 years old, statistical cognitive ability is above average in the whole lifespan and falls below average after age 46.

(2) Echo with the absorptive theory [6] and the knowledge theory [7], education could be an important approach for people to increase the statistical cognitive ability. As the education background is an evident factor affecting people's cognitive ability [21]. We find in our research that the years of education are highly positively correlated with statistical cognitive ability. Access to higher education is a means of improving statistical cognitive abilities. By receiving more education, people can improve judgment ability and delay the decline of cognitive ability. The statistical cognitive ability of the population with a college degree or above is significantly higher than that of the population with lower educational backgrounds. The difference of the statistical cognitive ability reaches peak at the age of 25, and the statistical cognitive ability of the elderly over the age of 60 remains above 5 points. In the whole life cycle, the statistical cognitive ability of the population without college education is significantly lower than that of the population with college education, and the gap is even more obvious after the age of 60.

(3) There is a positive correlation between parental education and children's statistical cognitive ability, but there is an obvious phenomenon of diminishing marginal returns. The correlation coefficient of parents with college degree or above on children's statistical cognitive ability is much smaller than that of parents with high school and below. Parents with higher educational background may spend more time and invest more money on children's education. This could indirectly affect children's statistical cognitive ability. According to the study of Ludeke et al. [22], parents' educational background has a latter-occurring influence on children's learning outcome. Such as parental education and education motivation can positively affect children's performance in education, which could help children achieve better cognitive ability.

(4) The statistical cognitive ability of women is higher than that of men before the age of 22, and the statistical cognitive ability of men is higher than that of women after the age of 23, and the rate of decline is lower than that of women. Echo with the study of McCarrey et al. [23], this finding also shows that gender is an important factor affecting statistical cognitive ability. Also, the older the age, the more obvious the difference is. But different from the findings of McCarrey et al., our finding indicates that women outperform men on statistical cognitive ability before the age of 23, which implies that other factors related to gender could affect women's statistical cognitive ability, such as family, occupation, etc.

Table 3
Robust Standard Error semiparametric regression and linear regression results.

Variable	Semiparametric Regression	Linear Regression
averageedu	0.056***	0.053***
	−0.007	−0.007
cfps2018eduy	0.843***	0.820***
	−0.005	−0.006
age	−0.098***	
	−0.002	
_cons	7.903***	
	−0.088	
N	23899	23899
R-sq	0.699	0.535

Note: *p < 0.1, **p < 0.05, ***p < 0.01.

The marginal contribution of this study is as follows: First, the existing literature mostly uses the method of parametric regression to study the influence of various factors on cognitive ability, but the cognitive ability variable is not normally distributed, and the parameter estimation method is usually biased, so non-parametric estimation is more reliable. We find the machine learning locally weighted regression algorithm is used to obtain the statistical cognitive curve closer to the real correlation, which can avoid over-fitting or under-fitting of parameter estimation and more accurately reflect the true correlation of data. Second, statistical cognitive ability is more and more important for the high-quality development of the whole society along with the arrival of the artificial intelligence society. It is more practical to analyze statistical cognitive ability independently from cognitive ability.

The findings of this research can help the educational system to recast the teaching philosophies of statistics based upon age and family background. Meanwhile, to fill the gap of this research, according to the limitations of our research, we'd expect the further exploration of the decline of female statistical cognitive ability after age 23 and the reasons of gender in deciding the changing curve of statistical cognitive ability. Also, we expect a cross-country comparison and multidisciplinary research to explain the influence of economy, technology development, and regional development on statistical cognitive ability.

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Data availability statement

The data we use is from the China Family Panel Studies (CFPS), which is available at the website http://www.isss.pku.edu.cn/cfps/download/login.

Ethics statement

This study has no declaration of interest.

CRediT authorship contribution statement

Kejie Zhao: Writing – review & editing, Writing – original draft, Software, Resources, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Wei Zang:** Writing – review & editing, Writing – original draft, Software, Resources, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Erman Nie:** Writing – review & editing, Writing – original draft, Resources, Methodology, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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