Visualization analysis of junior school students’ pubertal timing and social adaptability using data mining approaches

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HIGHLIGHTS

- Data mining is a new way to study pubertal timing and social adaptability problems.
- Clustering method can divide the similar students in many aspects into the same group.
- The radar chart shows that the role of each subscale is different.
- Data mining methods can help teachers to have detailed understanding of students.

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ABSTRACT

Pubertal timing and social adaptability are important research contents of adolescent mental health education. Traditional research methods mainly classify students based on the total score or average score of the scale, although this kind of method is simple easy to conduct, it can't make a more detailed analysis of the students. In this paper, data mining methods such as association rules and clustering are used to analyze the data of pubertal timing and social adaptability scale, some novel and meaningful conclusions are figured out from the analysis results that can't be obtained by the previous methods, and the analysis results are visualized to enhance readability. Association rule mining on basic attributes information, the pubertal timing group and the social adaptability levels were performed which can explore the relationship between the basic attributes information of the students, pubertal timing and the social adaptability. Fine-grained analysis of social adaptability by using clustering method was conducted which can divide the similar students into the same groups that is very useful for teachers to have a more in-depth, accurate and detailed understanding of students, make sure that the better classification can be obtained compared with the traditional analysis approaches. The work of this paper provides an effective guidance and a novel perspective for how to use data mining technologies to study the pubertal timing and social adaptability problems.

1. Introduction

The pubertal timing problem of the adolescents has been one of the most popular topics in the field of mental health in recent years. Adolescence is a critical period in the process of individual growth and development. In this period, the reproductive organs gradually mature, which also has a significant impact on the psychological and social adaptation of adolescents. The pubertal timing refers to the time when the developmental process of youth begins comparing the individual with the norm or a reference group, which can be divided into three stages: early maturity, moderate maturity and late maturity. In recent years, the incidence rate of precocious puberty has been increasing year by year and has become the focus of social concern. Moreover, the existing research works show that the early pubertal timing can lead to a series of internalization and externalization problems, including psychological and behavioral problems, obesity, anxiety and depression, peer relationship, drinking behavior, etc., among which, the social adaptation of adolescents is the most important problem.

Social adaptation is the sum of various psychological qualities needed by individuals to adapt to society, including interpersonal adaptation, study adaptation, life adaptation, etc. Social adaptation is not only an important part of health, but also an important part of...
teenagers’ early development, which significantly affects the individual academic achievement and individual development. Some research works proved that the overall social adaptability of the primary and secondary school students is low, which needs to be improved. The existing research works show that early pubertal timing will cause a series of psychological and behavioral problems in adolescence and even adulthood. “Maturity gap” is likely to appear when teenagers can’t reconcile the contradiction between biological maturity and social maturity, which will cause social adaptation difficulties. Viner et al. [1] also pointed out that teenagers with early pubertal timing are prone to have psychological problems such as adaptation difficulties due to their physical and mental development is not synchronized. Therefore, the social adaptation of students with early pubertal timing needs to be paid more attention.

Many emerging computer technologies including artificial intelligence, machine learning and deep learning are gradually used to study psychology related problems, such as pubertal timing, social adaptability.

The contributions of the paper are as the follows:

- We explored a new perspective based on data mining technology to study pubertal timing and social adaptability problems;
- We conduct fine-grained analysis of social adaptability by using clustering method which can make sure that the better classification can be obtained compared with the traditional analysis approaches;
- We provide a guidance for how to use data mining technologies to study the pubertal timing and social adaptability problems.

The other parts of this paper are organized as follows: Section 2 mainly introduces the related research works on pubertal timing, social adaptability and the computer technologies in psychology; Section 3 describes the research objects and data set; Section 4 talks about the association rules mining for pubertal timing and social adaptability; Clustering analysis for social adaptability is described in Section 5; Radar chart analysis for social adaptability is performed in Section 6; Section 7 summarizes this paper and points out the future promising research directions.

2. Related works

Many research works have been done on pubertal timing and social adaptability problems because of their importance in adolescent mental health. At the same time, many new research methods have emerged in the research of psychology, such as big data, artificial intelligence, data mining, machine learning and other computer related methods.

2.1. Pubertal timing

The existing research works show that the early pubertal timing can lead to a series of internalization and externalization problems, such as psychological and behavioral problems [2], depression [3], drinking behavior [4], etc. Hamlat et al. [5], Ullsperger et al. [6], Pomerantz et al. [7] and Kamper et al. [8] have made an in-depth study on the relationship between pubertal timing and psychopathology. Hamlat et al. [5] concluded that early pubertal timing may be a transdiagnostic risk factor for male and female in youth. Ullsperger et al. [6] found that females with early pubertal timing relative to their peers are likely to be at increased risk for psychopathology. The findings of Pomerantz et al. [7] proved that early pubertal timing was related directly with higher levels of anxiety, and higher levels of both anxiety and depressive symptoms were related indirectly with higher levels of relational aggression. Cousminer et al. [9] unveiled that some genomes are related with both body mass index (BMI) and pubertal timing. The relationship between pubertal timing and adolescent delinquency was studied in detail by Bucci et al. [10], the research results showed that the risk of adolescent delinquency will be increased by the early pubertal timing, while late pubertal timing will reduce the risk of adolescent delinquency. Dorn et al. [11] firstly proposed a new perspective that pubertal should be considered as a “window of opportunity” to understand and impact health, well-being and development. Yoshii et al. [12] described that a standard growth chart is necessary to evaluate an individual’s growth and constructed three longitudinal growth charts which correspond to pubertal timing. Sheng et al. [13] explored the association between different family factors and pubertal timing and obtained the conclusion that the influencing factors on children’s pubertal timing include whether being left-behind children, self-perceived of parental relationship and family economic conditions. Rudolph et al. [14] mainly studied the sex differences of the associations between pubertal timing and depression, their findings are very useful to understand the sex differences in depression across the adolescent transition.

2.2. Social adaptability

Krasilnikov et al. [15] explored the relationship between the academic performance of first year students and their social adaptation by using the exam grades and the data collected from the online social network. The research results showed that students’ early active participation in online social network in their freshman year is not conducive to learning while stable social activities are good for study. Wong et al. [16] proposed a novel and effective approach enabled by virtual reality technology to improve the social adaptation skills for children with autism spectrum disorder. Olivier et al. [17] obtained the conclusion through detailed studies that social adaptation is not only an important part of health, but also an important part of teenagers’ early development, which significantly affects the individual academic achievement and individual development. Duchesne et al. [18] tried to figure out the relationship between the students’ achievement goals (AGs) and psychological need satisfaction (PNS) through analyzing their academic and social adaptation. The findings showed that PNS is important for shaping adaptation and meeting the needs of autonomy and relevance contributes to social adaptation. Waters et al. [19] explored the influence of transition experiences on the social and emotional health of the adolescents, including transition to secondary school and at the end of the first year in new environment. Paradiso et al. [20] discussed the links between the onset of depression and social adaptation, the results showed that the social adaptation of the patients with early-onset and late-onset depression is poorer compared with the volunteers who are never-depressed, the social maladjustment of patients with late-life depression in remission may persist. Ukaaoyanya et al. [21] proposed a new valuable framework using symbolic interactionism to help the counselors to understand the socio-cultural dimensions of social adaptation among immigrant students.

2.3. The usage of advanced information technologies in psychology

Some researchers began to make studies about psychology from the perspective of big data [22, 23, 24]. Table 1 displays the summarization on the related works of the advanced information technologies in psychology. Zhang et al. [22] thought that unique advantages of big data provide new opportunities for mental health education for migrant children, it is necessary to build a cross departmental social adaptation database and information sharing platform for migrant children, and online information push and offline group counseling can improve the social adaptability of migrant children. Chen et al. [23] provided a practical guidance for psychology researchers to conduct psychology related research works from the perspective of big data and discussed the general framework of big data processing including data acquisition, data storage, data processing, data analyzing and data visualization. Landers et al. [24] proposed a new method called theory-driven web scraping which can be used to collect massive information from the internet for
psychologists, and also pointed out the matters needing attention in the process of data acquisition.

Yarkoni et al. [25] argued that traditional psychological research mainly focuses on explaining the causes of behavior, however, the accuracy of predicting future behavior is relative low. Yarkoni et al. [25] suggested that By focusing more on prediction than explanation using the lessons of machine learning, we can make better understanding of the behavior. Bleidorn et al. [26] pointed out that machine learning and big data technologies are very useful to develop personality assessment tools and they can effectively deepen and advance the understanding of personality. Walsh et al. [27] proposed a novel approach by using machine learning technology which can predicting the risk of suicide attempt. Mehta et al. [28] summarized the methods of automatic personality testing, and introduced the latest machine learning model for personality detection. Wang et al. [29] provided a useful and detailed guidance which can help the researchers to apply deep neural network technology to identify Children’s emotional and behavioral risk. Majumder et al. [30] attempted to use the method of deep learning to determine the author’s personality type according to the text content.

### Table 1. Related Works of Advanced Information Technologies in Psychology.

| Reference | Method | Target Problem | Pros | Cons |
|-----------|--------|----------------|------|------|
| [22]      | database and information sharing platform | social adaptability of migrant children | reduce the cost and achieve tangible results | information sharing across different sectors |
| [23]      | literature analysis | survey on big data research works in psychology | provide a practical guidance for psychology researchers from the perspective of big data | limited to test data (social media data) |
| [24]      | theory-driven web scraping | demystify web scraping methods to psychologists | provide detailed guidelines for web scraping in psychology research projects | lack of analysis on data validity and usefulness |
| [25]      | machine learning technology | better understanding of the behavior using machine learning technologies | conduct detailed analysis and comparison between explanation and prediction | lack of analysis on the performance of explanation and prediction in different psychological tasks |
| [26]      | machine learning technology | personality assessment and personality understanding | comprehensive reviews on machine learning to personality assessment | lack of experimental verification |
| [27]      | machine learning technology | predicting the risk of suicide attempt | improve accuracy and scale of suicide attempt detection using machine learning | lack of performance comparison of different machine learning algorithms |
| [28]      | machine learning technology | personality detection | overview of the machine learning models for personality detection | did not point out the future research directions and research topics |
| [29]      | deep learning technology | identify children’s emotional and behavioral risk | achieved the highest performance levels with accuracy (ACC) of .957 | precision of the proposed DNN is just 0.545 |
| [30]      | deep learning technology | personality detection | can detect the personality effectively from text | the accuracy is not high enough(0.62) |

![Fig. 1. The Description of the Students’ Attribute Information.](image)

3. Research objects and the data set description

#### 3.1. Research objects

The research objects are junior middle school students who are in grades 7, 8 and 9, there are totally 3605 students. The study is in line with the relevant scientific research ethics regulations and has obtained the ethical approval of the scientific research management department of Luoyang Normal University. We confirm that the informed consent was obtained from all participants for our experiments. The population attributes include gender, grade, home location and single child or not. Male students account for 56%, female students account for 44%, the students coming from countryside account for 58%, the students coming from city and town account for 42%, the distribution of the students in all grades is basically the same, while most of the students are non-single-child accounting for 87%. The detailed information is described in Fig. 1.

#### 3.2. Data set description

The data set contains three parts of information including the basic information of the students, the questionnaire results of Self-reported Pubertal Development Scale Chinese Version (C-PDS), the questionnaire results of Students’ Social Adaptability Scale (SAS).
The scale C-PDS is proposed by Zhu et al. [31] through the adjustment and the adaptation on the Pubertal Development Scale (PDS) designed by Petersen [32]. The scale can be divided into two versions according to gender differences: male version and female version which both contain five questions. Height, weight and skin change are the common problems in the two subscales. The male version scale contains two specific problems: voice and beard, while the female version scale contains two other specific problems: menstruation and breast development. The Cronbach $\alpha$ coefficient of male version scale was 0.63, and that of female version scale was 0.72. Among the scoring items of the scale, the menstrual change of female students was graded as the two levels, 1 point for “no menstruation” and 4 points for “menstruation”; The other items are graded as four levels: 1 point for “not yet started”, 2 points for “just started”, 3 points for “already obvious” and 4 points for “basically completed”. The PDS score can be figured out by summing up the scores of all items, then calculate its mean $\bar{x}$ and variance $s$. The students whose PDS is bigger than $\bar{x} + s$ are defined as the early-pubertal-timing-group, the students whose PDS is less than $\bar{x} - s$ are defined as the late-pubertal-timing-group, and the rest of the students are defined as the ordinary-pubertal-timing-group. For example, the mean $\bar{x}$ and variance $s$ of the male students are 12.52 and 2.92, if the PDS score of a student is bigger than 15.44, he will be assigned to early-pubertal-timing-group, if his PDS score is less than 9.6, he will be assigned to late-pubertal-timing-group, otherwise, he will be assigned to ordinary-pubertal-timing-group.

The scale SAS was designed by Chen et al. [33], including four subscales which are psychological energy scale, interpersonal adaptation scale, psychological superiority scale and psychological resilience scale, there are 70 items totally in SAS scale which includes 48 forward and 22 reverse scoring items. The total score is obtained by adding up the scores of all items with Likert’s five point scoring method, the higher the score is, the better social adaptability is. In this study, the Cronbach $\alpha$ of SAS scale is 0.95, and the Cronbach $\alpha$ of the subscale is bigger than 0.75, which has good reliability and validity and can effectively measure the level of students’ social adaptation.

4. Association rules mining for pubertal timing and social adaptability

Association rules mining has been successfully used in many fields such as transportation [34], marketing [35] and health [36]. In this section, we will try to apply association rules mining for pubertal timing and social adaptability.

4.1. Association rules mining for pubertal timing

According to the questionnaire results and grouping rule of C-PDS scale, all the students can be divided into three groups based on their PDS score. The early-pubertal-timing-group has 780 students, the ordinary-pubertal-timing-group has 2109 students and the late-pubertal-timing-group has 716 students. In order to have a deeper understanding of pubertal timing and find out the relationship between the basic attributes information of the students and the pubertal timing, we carried out association rule mining on basic attributes information and the C-PDS questionnaire results. For simplicity, we take the gender, grade, home location and single-child-or-not as the antecedent items, the pubertal timing group as the consequent item. The minimum support is set as 0.05 and the minimum confidence is set as 0.3, there are totally 63 association rules obtained through association rule mining operation. In order to be more intuitive, we use network diagram to show the association rules which is displayed in Fig. 2. Support represents the item size, confidence represents the edge size and the lift represents the edge color.

We can conclude that the association rules whose consequent item is ordinary-pubertal-timing-group have relative bigger support, the main reason behind this case is that the students belonging to ordinary-pubertal-timing-group account for a large proportion 58.5%. While most of the lift is relative small and even less than 1, this shows that the basic attributes information of the students has little impact on ordinary-pubertal-timing-group.

The association rules whose consequent item is early-pubertal-timing-group or late-pubertal-timing-group have the bigger lift which are our focus, the details are listed in Table 2. Taking Rule No. 1 as an example, its lift is 2.1441, this shows that “seventh-grade, non-single-child, male” play an important role in promoting “late-pubertal-timing-group”. The confidence 0.4250 represents that 42.58% of the students with the attributes “seventh-grade, non-single-child, male” belong to late-pubertal-timing-group. Rule No. 3 shows that 38.22% of the students with the attributes “eighth-grade, female, non-single-child” belong to early-pubertal-timing-group.

4.2. Association rules mining for social adaptability

In order to explore the relationship between the basic attributes information of the students, pubertal timing and the social adaptability, we carried out association rule mining on basic attributes information, the pubertal timing group and the social adaptability levels. Generally
Table 2. Association Rules for Pubertal Timing.

| Rule No. | Antecedent                                     | Consequent                     | Support | Lift    | Confidence |
|----------|------------------------------------------------|--------------------------------|---------|---------|------------|
| 1        | seventh-grade, non-single-child, male          | late-pubertal-timing-group     | 0.0558  | 2.1441  | 0.4258     |
| 2        | seventh-grade, countryside, male              | late-pubertal-timing-group     | 0.0705  | 1.9376  | 0.3920     |
| 3        | eighth-grade, female, non-single-child         | early-pubertal-timing-group    | 0.0535  | 1.7663  | 0.3822     |
| 4        | female, eighth-grade                          | early-pubertal-timing-group    | 0.0566  | 1.7656  | 0.382      |
| 5        | seventh-grade, non-single-child, male          | late-pubertal-timing-group     | 0.0840  | 1.2979  | 0.2435     |
| 6        | female, countryside, male                     | early-pubertal-timing-group    | 0.0796  | 1.6336  | 0.3534     |
| 7        | ninth-grade, male                             | early-pubertal-timing-group    | 0.0566  | 1.4778  | 0.3197     |
| 8        | female, non-single-child                      | early-pubertal-timing-group    | 0.1190  | 1.4022  | 0.3034     |

speaking, the higher the SAS score is, the better the social adaptability of the students is. The students can be divided into three groups based on their SAS score. There are totally 70 items in SAS scale, the score of each item between 1 point and 5 point, the final SAS score of each student is the average of all the scores of 70 items. The students whose SAS score is bigger than 4 are defined as the high group, the students whose SAS is less than 3 are defined as the low level group, and the rest of the students are defined as the medium level group. The high level group has 216 students, the medium level group has 2885 students and the low level group has 503 students. For simplicity, we take the basic attributes of the students and the pubertal timing as the antecedent items, the social adaptability level as the consequent item. The minimum support is set as 0.02 and the minimum confidence is set at 0.05, there are totally 280 association rules obtained through association rule mining operation. Fig. 3 displays the association rules using network diagram. Support represents the item size, confidence represents the edge size and the lift represents the edge color.

The association rules whose consequent item is low level or high level are of our interest, the details are listed in Table 3. The results show that pubertal timing has little effect on social adaptability. Taking Rule No. 2 as an example, its lift is 1.2663, this shows that “ninth-grade, non-single-child” can promote “low-level” by 26.63%. The confidence 0.177 represents that 17.7% of the students with the attributes “ninth-grade, non-single-child” belong to low level group.

4.3. Running time analysis

Fig. 4 displays the running time of the association rules mining for pubertal timing and social adaptability. The results show that the running time decreases as the support increases given a confidence (0.3). The reason is that the smaller the support is, the larger cardinality of the candidate frequent itemset will be. We can also find that the running time of social adaptability is bigger than that of pubertal timing, because the item number of social adaptability is 7 and the item number of pubertal timing, the former is greater than the latter.

5. Clustering analysis for social adaptability

The traditional analysis approaches for social adaptability are mostly based on the statistical methods, and the students are divided into three groups according to their SAS scale scores. The description of subsection 4.2 shows that the distribution of the students in different groups is extremely uneven, medium level group accounts for 80%.

However, the traditional grouping rules are based on the mean or sum of the 70 item scores of SAS scale, this kind of analysis method is relatively rough. The following cases often occur: the mean values of the 70 item scores for student $s_{123}$ and $s_{124}$ are the same or close with each other, so $s_{123}$ and $s_{124}$ will be regarded as the same group. While the truth is that the scores of most corresponding items are different,
Table 3. Association Rules for Social Adaptabley.

| Rule No. | Antecedent                          | Consequent | Support     | Lift   | Confidence |
|----------|-------------------------------------|------------|-------------|--------|------------|
| 1        | ordinary-pubertal-timing-group, city-and-town | high-level | 0.0214      | 1.3833 | 0.0829     |
| 2        | ninth-grade, non-single-child        | low-level  | 0.0505      | 1.2663 | 0.1770     |
| 3        | city-and-town, non-single-child     | high-level | 0.0252      | 1.1783 | 0.0706     |
| 4        | city-and-town                       | low-level  | 0.0688      | 1.1632 | 0.1626     |
| 5        | female                              | low-level  | 0.0693      | 1.1361 | 0.1589     |
| 6        | ordinary-pubertal-timing-group, male| high-level | 0.0241      | 1.1335 | 0.0679     |
| 7        | seventh-grade, late-pubertal-timing-group, male | medium-level | 0.0568   | 1.1285 | 0.0301     |
| 8        | ninth-grade                         | low-level  | 0.0677      | 1.4460 | 0.2022     |

Table 4. The average distance of student pairs within cluster.

|       | traditional | cluster10 | cluster12 | cluster14 | cluster16 | cluster18 | cluster20 |
|-------|-------------|-----------|-----------|-----------|-----------|-----------|-----------|
| value | 9.16        | 8.16      | 8.25      | 8.02      | 7.93      | 7.95      | 8.03      |

Fig. 5. The Item Score of Student No.3135 and Student No.3414.

The average distance of student pairs within cluster by traditional and clustering approach. Fig. 6 shows the comparisons of the item scores for two pairs of students. The average distance of student pairs within cluster under different cluster number, the smaller the average distance is, the higher the cohesion of the cluster is and representing better clustering effect. The final cluster number is chosen as 16 according to the result of Table 4.

Therefore, students with similar characteristics should be assigned to the same cluster. We can conclude that clustering is an effective and better approach for analyzing the junior school students’ adaptability according to the previous description and analysis results, it can divide the similar students into the same groups, that is very useful for teachers to have a more in-depth, accurate and detailed understanding of students.

6. Radar chart analysis for social adaptability

Radar chart was originally a kind of financial analysis report and it is also known as network chart or spider chart, it is considered to be a kind of chart which can display multi-dimensional data. The SAS scale contains four subscales including mental dominance, mental energy, interpersonal adaptation and mental resilience, each subscale also has some different aspects. In order to conduct more in-depth analysis on the SAS scale questionnaire result we try to perform radar chart analysis on the subscales and the different aspects for each subscale.

6.1 Overall results and the subscales

Fig. 8 displays the radar chart of the overall results and the four subscales including mental dominance, mental energy, interpersonal adaptation and mental resilience. For the students in high-level group, the value of interpersonal adaptation is 4.38 which is the best among the four subscales, and the value of mental dominance is 4.02 which is the worst among the four subscales. Interpersonal adaptation is also the best for the students in medium-level group and low-level group. While the worst subscale for medium-level students is mental dominance and that for the low-level students is mental energy. Overall, Interpersonal
adaptation has the greatest impact on social adaptability and occupies a dominant position. The teachers should pay more attention on different subscales for different group students that can help teachers understand students better and carry out targeted counseling.

### 6.2. Aspects for different subscales

Table 5 lists the aspects of different subscale. In order to understand the effect of different aspects on each subscale, we performed radar chart analysis on each subscale, Fig. 9 displays the detailed analysis results. Fig. 9-(a) shows that sense of control plays a leading role in mental dominance subscale for all levels of students, and the values of autonomy are the smallest. Fig. 9-(b) shows that different aspect including motive power, ability and vitality plays different roles in mental energy subscale. The values of motive power for high-level and medium-level students are the biggest, and the value of ability is 1.93 which is the worst for low-level students on mental energy subscale. Fig. 9-(c) shows that altruistic tendency is the most important for interpersonal adaptation subscale on all levels of students, and the value of sociability is 4.17 which is the worst for high-level students on interpersonal adaptation subscale. Fig. 9-(d) shows that different aspect including self-control, challenging, flexibility and optimistic tendency plays different roles in mental resilience subscale for high-level and medium-level students, and optimistic tendency is the best and flexibility is the worst. However, all the aspects play basically the same role in mental resilience subscale for low-level students.

### 7. Conclusions

In this paper we conduct association rules mining and clustering analysis on pubertal timing and social adaptability of junior school students. The analysis results show some new and meaningful conclusions which are different from the results of the traditional methods. In the future, we will further strengthen the cross integration of information technology and psychology, pay more attention to the collection and accumulation of psychology related data. Data driven social adaptability analysis and mining based on students’ daily behavior data and academic records using artificial intelligence technologies such as deep learning and machine learning will be one of the important research directions in the future.
Table 5. Aspects of Different Subscales.

| Subscale            | Aspect 1       | Aspect 2       | Aspect 3       | Aspect 4       |
|---------------------|----------------|----------------|----------------|----------------|
| mental dominance    | self-confidence| sense of control| autonomy       |                |
| mental energy       | motive power   | ability        | vitality       |                |
| interpersonal adaptation | sociability | trust          | social acceptance | altruistic tendency |
| mental resilience   | self-control   | challenging    | flexibility     | optimistic tendency |

Fig. 9. The Aspects for Different Subscales.

Declarations

Author contribution statement

Ruiling Zhang: Conceived and designed the experiments. Youzhong Ma: Performed the experiments; Analyzed and interpreted the data; Wrote the paper.
Yongxin Zhang: Contributed reagents, materials, analysis tools or data.

Declaration of interests statement

The authors declare no conflict of interest.

Data availability statement

Data will be made available on request.

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Additional information

The data used to support the findings of this study are available from the corresponding author upon request in compliance with relevant requirements.

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