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Research on Movement Behavior Analysis and Mental Health Interventions Based on Big Data

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ABSTRACT

With the vigorous development of big data technology, exploring its potential in sports behavior analysis and mental health intervention has emerged as a crucial research direction. This experiment enrolled 62 participants aged 18–60 years who were randomly assigned to an observation group and a control group based on a pre-/post-experimental control group design. Exercise intensity, frequency, and duration were monitored via wearable devices, and mental health status was evaluated using eight indicators, including the Self-Rating Depression Scale and the Self-Rating Anxiety Scale. The participants in the observation group received personalized mental health interventions based on big data analysis, whereas those in the control group maintained their usual lifestyle. Data were analyzed using SPSS, independent samples t-tests, and paired samples t-tests. Results indicate that after the intervention, the observation group exhibited significant improvements in exercise metrics along with reduced scores for depression, anxiety, and sleep quality and increased scores for life satisfaction and psychological resilience. Statistically significant differences were observed between the scores of the two groups, thus confirming the effectiveness of the intervention program.

KEYWORDS
big data, physical activity behavior, mental health, intervention

INTRODUCTION

In recent years, with its powerful information processing and analysis capabilities, big data technology has been widely used in many fields, such as medical and health care, education, and transportation, and has achieved remarkable results [1]. At the same time, mental health issues have attracted growing attention from society. Data from the World Health Organization show that the incidence of mental illness is on the rise globally, and mental health has become an important factor affecting public quality of life and the harmonious development of society [2]. As an effective intervention, exercise demonstrates a complex and close relationship with mental health. Regular exercise can trigger the brain to secrete neurotransmitters, such as endorphins and serotonin, which effectively relieve anxiety and depression. However, some differences are noted in the mechanisms and effects of different types of exercise, such as aerobic exercise and group exercise, on mental health [3]. For instance, while aerobic exercise can improve cognitive function, group exercise can enhance social skills and sense of belonging [4]. In addition, traditional exercise behavior analysis and mental health intervention methods are unable to integrate and deeply mine massive data, thus presenting challenges in achieving a precise and personalized intervention.

Sports behavior analysis and mental health intervention based on big data have become critical for two reasons. On the one hand, traditional intervention methods are unable to comprehensively and dynamically capture individual exercise behavior characteristics and mental health changes, resulting in insufficient targeted intervention measures. Big data can integrate multi-source data to achieve an accurate analysis of exercise behavior and provide personalized mental health interventions [5]. On the other hand, the complexity and diversity of mental health issues urgently require innovative intervention models, but the current application of big data technology in this field still faces multiple bottlenecks. First, the collection of exercise behavior data mostly relies on wearable devices, but each device shows different accuracy and compatibility. Second, health data involve sensitive personal information that are at high risk of being disclosed without authorization. Third, existing algorithms are generally incapable of accurately mining the complex characteristics of exercise behavior and mental states. Fourth, compound talents who are proficient in big data and in sports and psychological disciplines are generally lacking.

The vigorous development of big data technology and mental health problems have attracted increasing scholarly attention. Previous studies have mainly focused on three aspects, namely, big data technology, the application of big data technology in sports behavior analysis, and the application of big data technology in mental health. In terms of big data technology, Li studied the application of such technology in constructing a talent collaborative training mechanism and pointed out that the construction and use of an intelligent teaching platform based on big data can significantly improve students' overall performance [6]. In the digital economy context, Wu analyzed the problems in the application of big data technology in business administration and proposed some suggestions for improvement [7]. Li discussed several methods of applying big data technology in improving the emergency rescue ability of scenic spots and demonstrated its significant application potential [8]. In terms of applying big data technology in sports behavior analysis, Tseng pointed out that mobile medical care based on big data technology has become an important trend in medical and health care. The rapid development of wearable and sensing technologies has enabled the collection of sports and health-related information [9]. Stergiou explored the combination of mobile Internet of Things and cloud computing and investigated their common characteristics and contributions to the development of big data technology [10]. Sellami analyzed molecular big data in sports science and concluded that big data technology plays an important role in sports physiology, such as in determining the biology and gene composition of athletes, which are known to affect their physical activity, speed, neuromuscular coordination, and endurance [11]. In terms of applying big data technology in mental health intervention, Qu analyzed the influence of mobile phone dependence on college students' mental health under the background of big data and found a significant positive correlation between mobile phone dependence and depressive symptoms among college students regardless of their gender [12]. Cai discussed the opportunities and challenges of mental health education in colleges and universities from the perspective of big data and highlighted several challenges, such as data privacy and security issues, insufficient data analysis and interpretation capabilities, and lack of technical facilities and talent support [13]. Shi analyzed the application of models based on big data technology in monitoring and evaluating college students' mental health and found that these models can accurately and quickly evaluate the basic psychological state of students [14].

While the above studies have explored the application of big data technology from multiple perspectives, relatively few studies have simultaneously explored the application of such technology in sports behavior analysis and mental health intervention. One exception was Choi, who combined big data with comparative analysis to understand the psychological behavior of the elderly when participating in leisure sports [15]. Moreover, only a few studies have considered how fundamental technical issues, such as algorithm bias and data quality, can impact their analysis results. These studies are mostly theoretical and lack systematic solutions for real-world scenarios. The insufficient interdisciplinary integration in the literature also fails to fully leverage the potential of big data technology across various fields.

The current research is motivated by the aforementioned gaps. Deeply mining big data to uncover the potential connections between sports behavior and mental health not only fills gaps in interdisciplinary research but also overcomes the limitations of traditional intervention methods, thereby improving data quality and algorithm accuracy. Additionally, developing systematic solutions based on big data can yield personalized interventions, thus bridging the gap between research and practice and providing scientific and practical technical support and theoretical guidance for promoting the overall physical and mental health of the population.

EXPERIMENTAL

Materials and Methods

Materials

To ensure the validity and reliability of the experimental results, the selection of research objects followed a rigorous and systematic design and implementation process.

First, the research team used various channels to recruit participants who satisfied the experimental requirements. For instance, recruitment announcements were posted around universities, communities, enterprises and other places. These announcements described the research purpose, process, participation requirements, and possible benefits in detail to attract participants. During the recruitment process, the research team actively communicated with the applicants and answered their questions to improve their understanding and trust in the research.

The applicants were then screened based on several inclusion and exclusion criteria. Only those applicants aged 18–60 years were considered given that mental health problems are most common in this age group. These applicants should also demonstrate good physical function and normal exercise ability in order to participate in the sports intervention designed for the experiment and to obtain accurate exercise behavior data. They should have no history of serious physical diseases and mental disorders that could interfere with their sports and mental health in order to ensure that the research results can accurately reflect the effects of sports behavior analysis and mental health intervention based on big data. These applicants were individually asked about their medical history and recent physical examination results and were subjected to a face-to-face physical function assessment to determine whether they meet the above inclusion criteria.

Meanwhile, those applicants who recently participated in similar mental health intervention projects were excluded from the study to prevent the past intervention measures from confounding the results of this study. Those applicants with conditions that may be exacerbated by their use of smart wearable devices, such as skin allergies and severe arrhythmia, were also excluded to ensure the integrity and accuracy of data collection [16]. During the screening process, the research team communicated with the attending doctors of the applicants to ensure the accuracy of the collected information.

After the screening process, the participants were divided into two groups following a specific procedure to ensure the scientific and reproducible nature of the randomization. First, a total of 62 participants were deemed eligible for the study. Second, a computerized randomization program was used to achieve a complete randomization. During this operation, each participant was assigned a unique number ranging from 1 to 62. The program then generated 62 random numbers that were later sorted. The first 31 participants with corresponding numbers were placed in the observation group, while the other 31 participants were placed in the control group.

Methods

Experimental method. Pre-test stage: Before the experiment, the following eight test indicators were measured in the observation group and the control group, and the baseline data were collected as shown in Table 1. These two groups were evenly distributed in terms of demographic characteristics, such as age, gender, education level, and marital status, thereby laying a solid foundation for guaranteeing the comparability of the experimental results. Then, according to the results obtained from the evaluation indicators, the intergroup homogeneity analysis can be carried out more comprehensively, which is conducive to the advancement of the research.

Intervention stage: The individual sports behavior data of the participants in the observation group were collected and analyzed in real time with the help of the big data platform, and then personalized mental health intervention plans were generated according to the analysis results, including exercise plan adjustments, psychological counseling courses, and peer support activities. The intervention period lasted for eight weeks. Meanwhile, in the control group, the participants maintained their usual living conditions, and sports behavior analysis and mental health intervention based on big data were not carried out.

Post-test stage: After the intervention, the indicators of the participants in both groups were measured again, and the post-test data were collected.

Table 1. Comparison of two sets of baseline data

Demographic characteristics	Observation group (n = 31)	Control group (n = 31)
Age (year, $\bar{\mathbf{x}} \pm \mathbf{s}$)	28.5±4.2	27.9± 3.8
Sex (male/female, n)	16/15	17/14
Educational level (junior college and below / undergraduate and above, n)	12/19	13/18
Marital status (married/ unmarried, n)	9/22	10/21

Evaluation method. Baseline data for the eight test indicators were collected in both groups. Movement behavior data were collected using the Apple Watch Series 8 (sampling rate 1 time per second) and the Polar H10 heart rate belt (sampling rate 1000 times per second), while mental health data were collected using standardized scales. The observation group utilized a big data platform to receive real-time data from the Apple Watch and Polar H10 transmitted to the Huawei Cloud platform. After the analysis, personalized mental health intervention plans were developed, including adjustments to the exercise plan. This intervention mechanism aligns well with theory of translational model (TTM). The big data platform analyzed user movement data to accurately identify their stage of behavioral change (e.g., pre-intention, intention, preparation, action, and maintenance) and then matched them with the appropriate strategies. The platform also disclosed information about the benefits of exercise to those participants in the pre-intention stage to enhance their awareness, formulated a progressive exercise plan for those participants in the preparation stage, and reinforced consistent behavior through real-time data feedback for those participants in the action stage. If a user fails to meet the target exercise frequency for three consecutive days, then the system would automatically reduce the intensity goal and send motivational messages to prevent behavior interruption due to overly high expectations. This dynamic intervention based on TTM allowed the exercise plan to intelligently adapt to the user's behavioral stage, thereby significantly enhancing the precision and sustainability of the intervention. Meanwhile, the participants in the control group maintained their same living conditions and only wore the Xiaomi Band 7, which does not transmit data.

Exercise frequency, or the number of times one has engaged in exercise every week, reflects the regularity and continuity of individual exercise. Exercise duration records the duration of each exercise and analyzes the amount of time that individuals spend in exercise. The Self-Rating Depression Scale (SDS) was used to evaluate the degree of individual depression symptoms. A score of 50 or above indicates the presence of depression symptoms, and a higher score corresponds to more serious symptoms. Meanwhile, the Self-Rating Anxiety Scale (SAS) was used to evaluate individual anxiety symptoms. A score of 50 or above indicates the presence of anxiety symptoms, and a higher score corresponds to more serious symptoms. The Satisfaction with Life Scale (SWLS) was used to evaluate the participants' satisfaction with their own lives on a scale of 5 to 35, with a higher score indicating a higher satisfaction [17]. The Connor–Davidson Resilience Scale (CD-RISC) was used to measure the resilience of participants in the face of pressure and frustration. The scale has a total score of 100, with a higher score indicating a stronger resilience [18]. The Pittsburgh Sleep Quality Index (PSQI) was used to evaluate the sleep quality of the participants on a score of 0–21, with a higher score corresponding to a worse sleep quality. The technology input indicators include the costs for big data platform development, cloud services, and purchase of Mi Bands, while the health benefit indicators mainly include the change in SDS scores.

Analysis of covariance was performed to eliminate the interference of baseline differences on the experimental results during the data processing and analysis. This procedure involved incorporating the baseline data of each test indicator as covariates into the model, thereby controlling for baseline differences and assessing the impact of the intervention measures on the observation and control groups. To address missing data, the mechanism of data missingness was initially examined. Specifically, if the data are completely randomly missing, then mean imputation was performed to calculate the mean of the variable within the group and then fill in the missing values. If the data are missing at random, then multiple imputation methods were employed, and predictive models were constructed based on other related variables to generate multiple imputed datasets. These datasets were then analyzed separately, and their results were combined to ensure the robustness and reliability of the analysis. Throughout the data processing and analysis phase, strict adherence to privacy protection principles was maintained. The data collected from the participants were anonymized by removing names, ID numbers, and other identifiers and by using numbers to refer to these participants in the subsequent operations. The collected data were stored in encrypted cloud servers with multi-layer access permissions that only core members of the research team could bypass. These data were regularly backed up, and security checks were performed.

RESULTS AND DISCUSSION

Exercise Intensity

Figure 1 shows the statistical results for exercise intensity, that is, the average heart rate of the two groups before and after the intervention. Only a slight difference can be observed between these groups in terms of exercise intensity before the intervention, but after the intervention, the average heart rate of the participants in the observation group was higher than that of the participants in the control group. The independent samples t-test analysis reveals a significant difference in the change of indicators between these groups ($t = 5.21$, $p < 0.001$). Specifically, the exercise intensity of the observation group was significantly improved because the intervention scheme based on big data dynamically adjusted the exercise plan according to real-time data, such as individual heart rate and pace. For example, if the system monitors that the user's heart rate is in a low range for a long time, then the system sends suggestions to increase the intensity of exercise (e.g., increasing the running speed and intensity of strength training) and guides the participants to gradually adapt to higher-intensity exercise. However, the control group did not receive such intervention, and their exercise habits did not change, thus resulting in no obvious improvement in their exercise intensity.

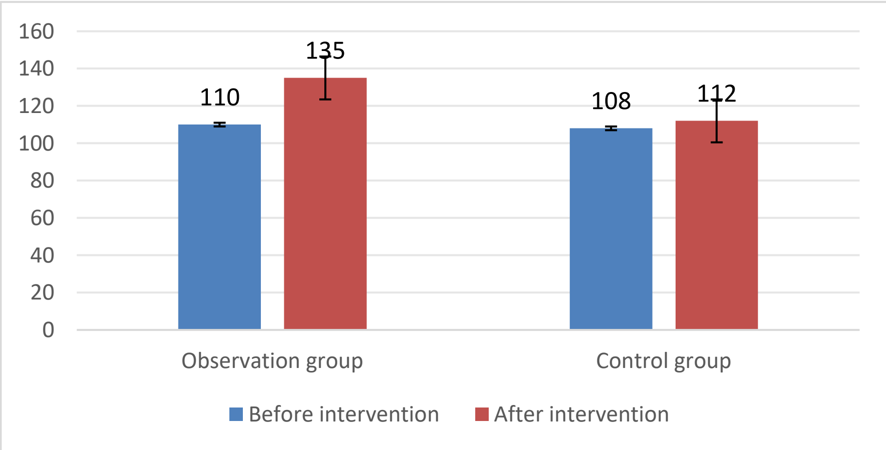

Figure 1. Comparison of exercise intensity before and after the intervention in the two groups of participants

Motion Frequency

Figure 2 shows the statistical data for the exercise frequency of the two groups before and after the intervention. Before the intervention, both groups exercised twice a week, while after the intervention, the observation group exercised four times a week. The independent sample t-test reveals a significant difference between these groups after the intervention ($t = 3.1$, $p < 0.01$). Under the personalized intervention driven by big data, the changes of indicators in the observation group significantly differed from those in the control group. Specifically, the frequency and duration of exercise in the observation group increased because big data analysis can integrate the participants' schedules, exercise history, and other data to formulate personalized exercise reminders and plans. Upon detecting that the participants have not exercised for several days in a row, the system would automatically send reminders and provide short-term exercise courses that fit their schedules, thereby encouraging the participants to increase their frequency and duration of exercise [19]. Given that the participants in the control group received no personalized guidance driven by big data, they did not actively change their irregular movement state.

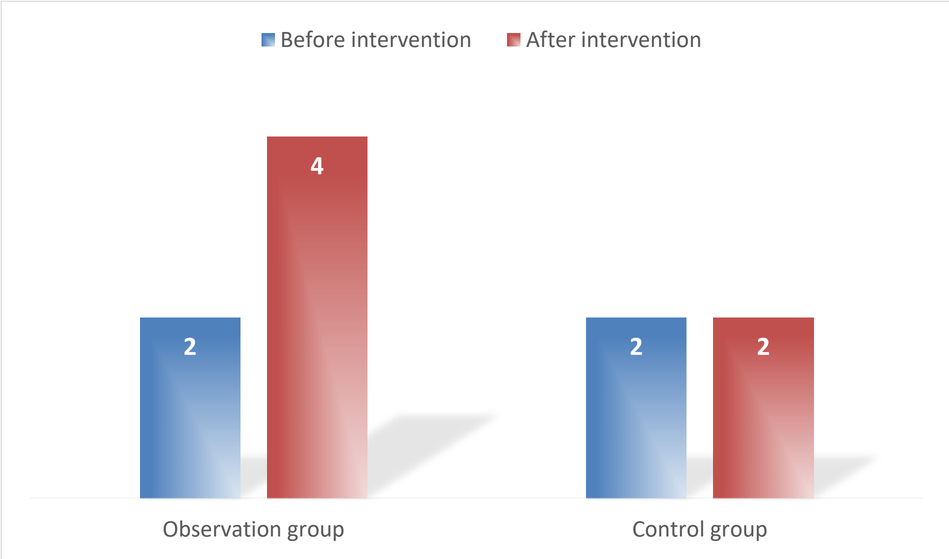

Figure 2. Comparison of exercise frequency before and after the intervention in the two groups of participants

Duration of Exercise

Figure 3 shows the statistical data for the exercise duration of the two groups before and after the intervention. Before the intervention, only a slight difference in exercise duration was observed between the two groups, but after the intervention, the exercise duration of both groups increased, with the observation group showing a more significant degree of increase. The independent samples t-test reveals a significant difference in the changes of indicators between these groups ($t = 5.12$, $p < 0.001$). Specifically, the observation group witnessed a +14.7 improvement after the intervention, which was significantly higher than the +3.6 improvement reported in the control group, thus validating the effectiveness of the intervention model.

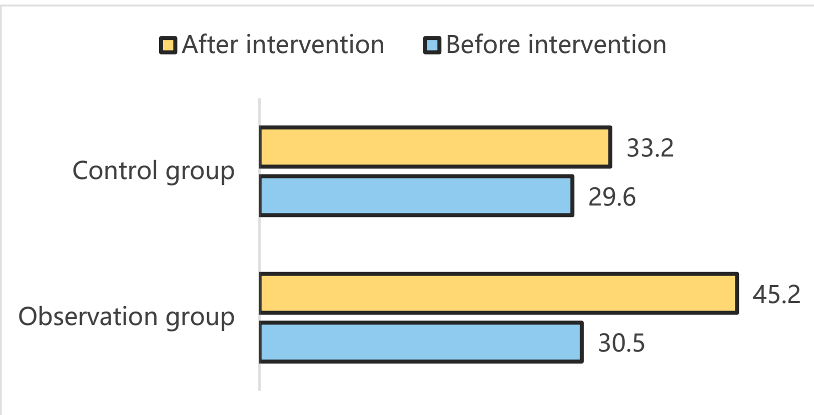

Figure 3. Comparison of exercise duration after the intervention in the two groups of participants

Self-Rating Depression Scale Score

Figure 4 illustrates the SDS scores of the two groups of participants before and after the intervention. Both groups reported similar depression levels before the intervention, but after the intervention, their SDS scores decreased, with the observation group showing a more significant reduction. The independent samples t-test reveals a significant difference in the changes in SDS scores between these groups ($t = 6.82$, $p < 0.001$). The decrease in SDS scores in the observation group was primarily driven by the synergistic effect of the big data intervention plan, exercise behavior analysis, and psychological counseling. Increasing the intensity, frequency, and duration of exercise not only promotes the secretion of neurotransmitters such as endorphins to alleviate negative emotions but also effectively regulates cortisol levels [20]. As a stress hormone, cortisol can exacerbate depressive symptoms when chronically elevated, while regular exercise can reduce the basal secretion of cortisol, thereby reducing the body's stress response and improving emotional state from a physiological perspective. The system also recommends targeted psychological counseling courses based on the scores of psychological scales, thus helping the participants learn emotional regulation techniques. The control group, which did not receive effective intervention, saw no significant improvement in their negative emotions.

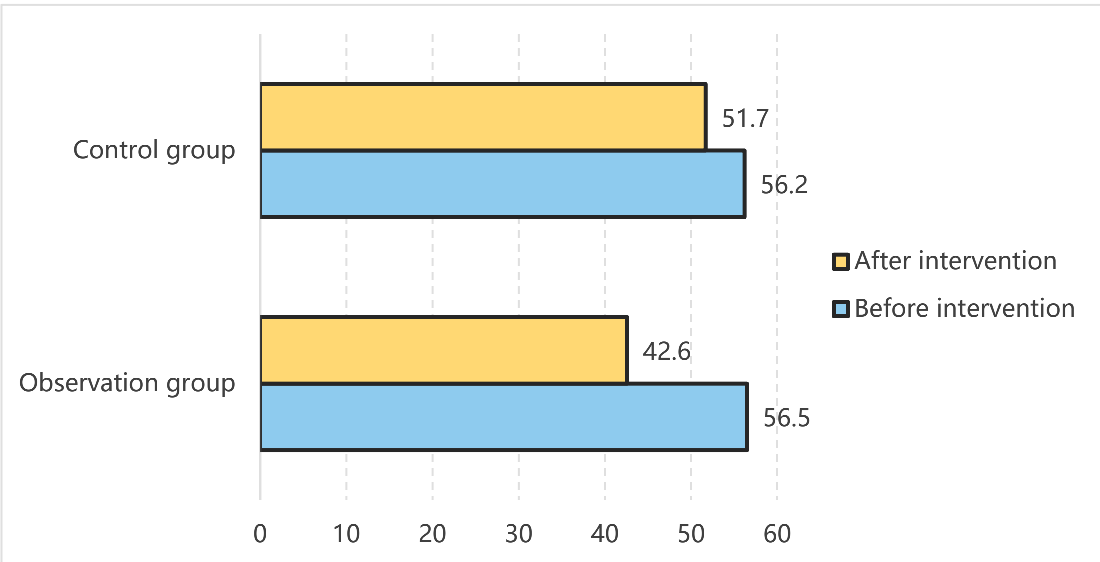

Figure 4. Comparison of SDS scores before and after the intervention in the two groups of participants

Self-Rating Anxiety Scale Score

Figure 5 illustrates the SAS scores of the two groups of participants before and after the intervention. Both groups reported similar anxiety levels before the intervention, but following the intervention, their SAS scores decreased, with the observation group reporting a more significant reduction. The improvement in the SAS score of the observation group can be attributed to the synergy between big data precision intervention and psychological counseling courses and to physiological mechanisms. Regular exercise effectively balances the autonomic nervous system, thus reducing the overexcitement of the sympathetic nervous system. During exercise, the body activates the parasympathetic nervous system, which slows down heart rate and lowers blood pressure, thereby reducing the release of stress hormones such as norepinephrine. Exercise can also reduce cortisol levels in the blood, thereby alleviating anxiety caused by prolonged stress. This combination of physiological regulation and psychological intervention leads to better outcomes in reducing anxiety symptoms for the observation group.

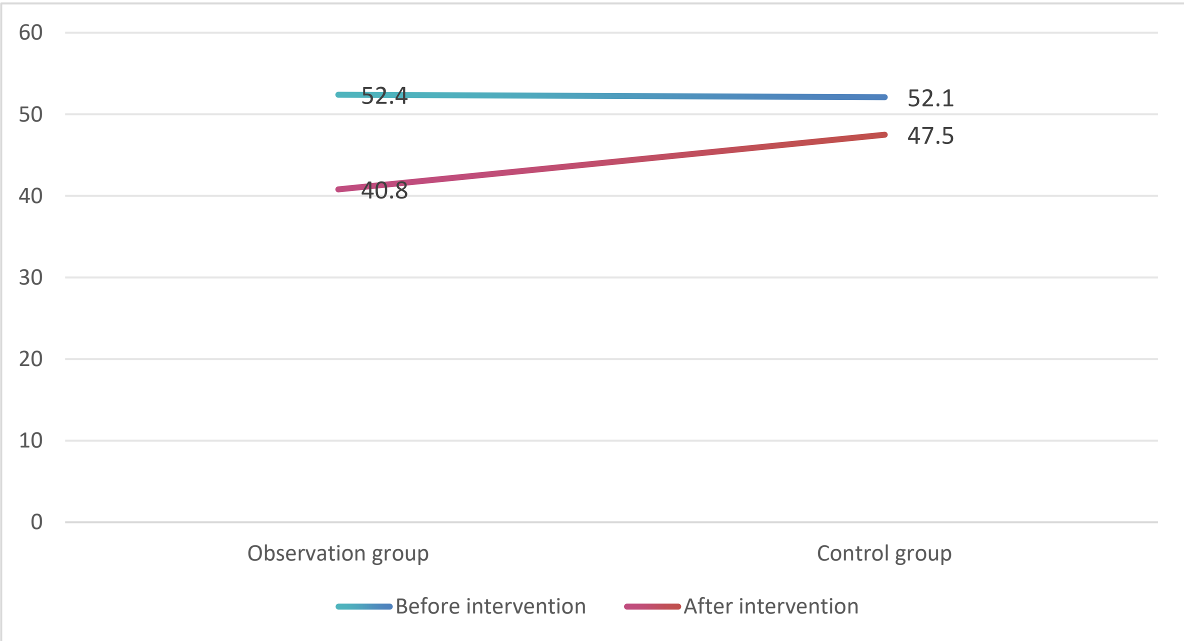

Figure 5. Comparison of SAS scores before and after the intervention in the two groups of participants

Satisfaction with Life Scale Score

Figure 6 shows the SWLS scores for the two groups of participants before and after the intervention. These two groups showed only a slight difference in their SWLS scores before the intervention, but after the intervention, the scores of the observation group significantly increased. The independent samples t-test reveals a significant difference between these groups in their change of indicators ($p < 0.01$). The improvement in life satisfaction in the observation group can be attributed to two factors. First, exercise improves one's physical function and mental state, thus enhancing the participants' self-efficacy. Second, the social elements in the big data intervention program, such as peer support activities, expanded the participants' social circles, thereby increasing their sense of social support and their satisfaction with life [21]. By contrast, due to the absence of any intervention, the participants in the control group did not experience any positive changes in their lifestyle and showed no significant improvement in their life satisfaction.

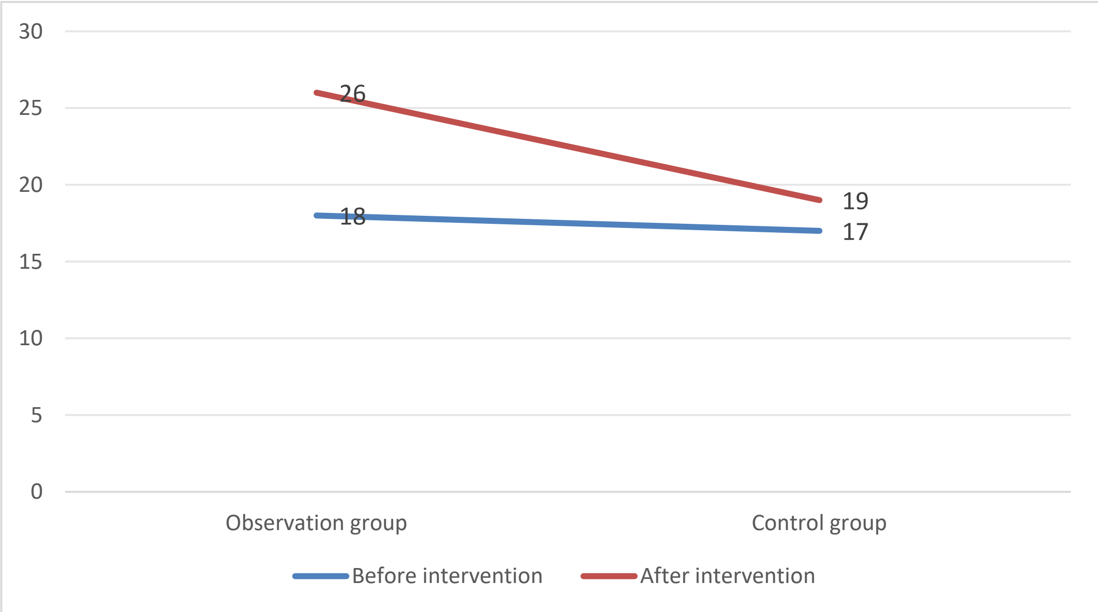

Figure 6. Comparison of SWLS scores before and after the intervention between the two groups of participants

Connor–Davidson Resilience Scale Score

Figure 7 presents the CD-RISC scores of the two groups of participants before and after the intervention. Both groups showed minimal differences in their scores before the intervention, but after the intervention, the CD-RISC scores of the observation group significantly increased. The independent samples t-test reveals a significant difference in the changes of indicators between these groups ($t = 4.35$, $p < 0.001$), with the improvement in the observation group (+12.6) being significantly higher than that in the control group (+4.6), thereby confirming the intervention's value. The psychological resilience of the observation group also increased not only due to regular exercise training and counseling courses but also because regular exercise promotes the secretion of the brain-derived neurotrophic factor, which facilitates the growth, survival, and differentiation of neurons, enhances brain plasticity, and allows individuals to more flexibly adjust their cognitive and emotional responses to stress and setbacks. Exercise also regulates the balance of neurotransmitters in the body by increasing serotonin levels, which helps stabilize emotions, reduce sensitivity to negative events, and offer physiological support for enhancing psychological resilience, thus allowing individuals to become more adaptable to stress and setbacks [22].

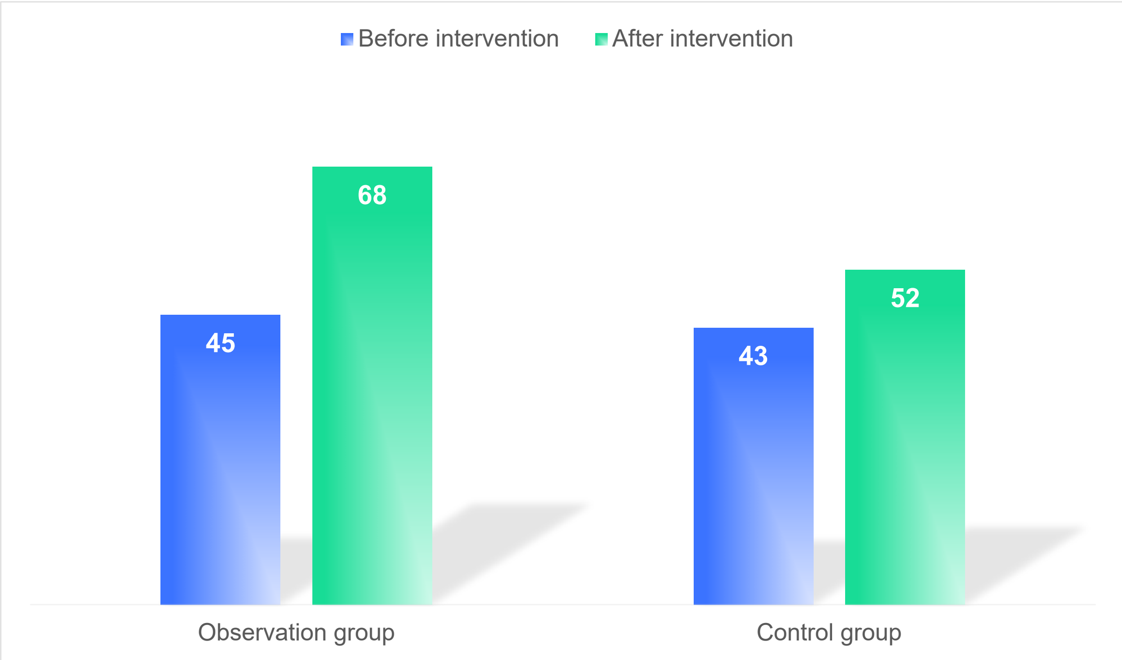

Figure 7. Comparison of CD-RISC scores before and after the intervention in the two groups of participants

Pittsburgh Sleep Quality Index Score

Figure 8 shows the PSQI scores of the two groups of participants before and after the intervention. These groups only showed relatively small differences in their PSQI scores before the intervention, but after the intervention, the observation group reported a significantly greater reduction in its PSQI scores compared with the control group, thereby indicating that the former showed better improvements in sleep quality after the intervention. The independent samples t-test reveals a significant difference in the changes of indicators between these groups ($t = 3.27$, $p < 0.01$). The improvement in sleep quality in the observation group can be attributed to the effective utilization of physical exertion and regulation of the biological clock through well-planned exercise in the big data framework, while the alleviation of depressive and anxious moods also reduced interference with their sleep. By contrast, due to the lack of optimized physical activity and psychological state in the control group, the participants reported no significant improvements in their sleep quality.

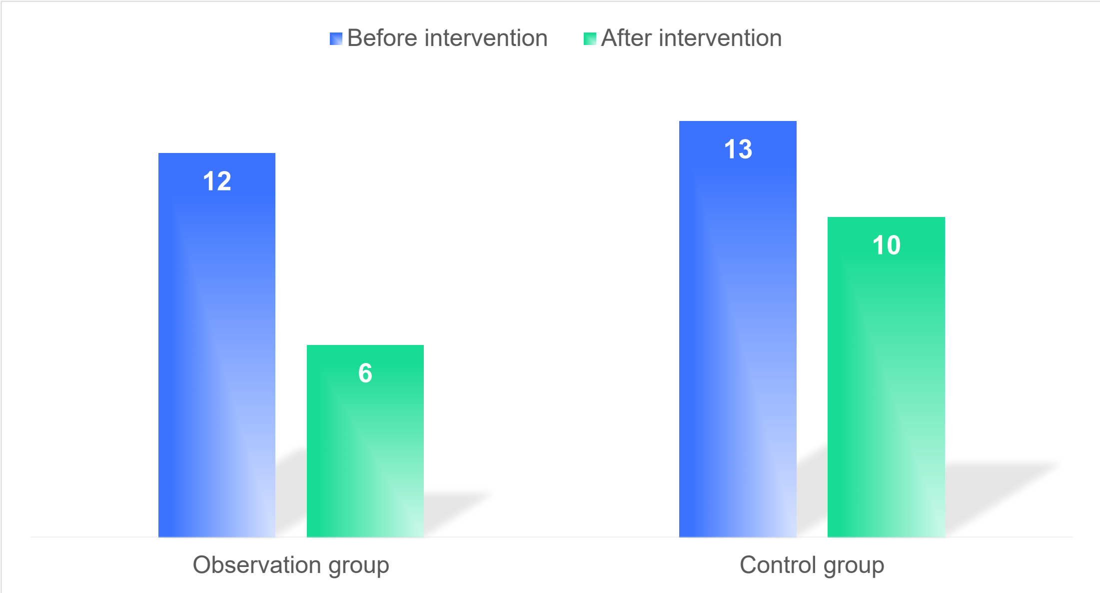

Figure 8. Comparison of PSQI scores before and after the intervention in the two groups of participants

Cost-Effectiveness Results

In terms of cost effectiveness, the research team purchased Apple Watch Series 8 and Polar H10 devices and developed a big data platform and cloud services for the participants in the observation group, amounting to expenses of approximately 800,000 yuan. Meanwhile, the control group was equipped with only the Xiaomi Band 7, which cost about 12,000 yuan. Although the investments in the observation group were much greater than those in the control group, such investments significantly improved the depressive symptoms of the participants.

CONCLUSION

Through a group-controlled experiment involving 62 participants, this study confirmed the significant effects of a data-driven analysis of physical activity behavior combined with mental health intervention programs. In terms of physical activity, the participants in the observation group showed noticeable improvements in their exercise intensity, frequency, and duration after the intervention. Big data can accurately analyze individual movements, create personalized exercise plans, and effectively guide the participants to develop regular exercise habits. On the mental health front, the participants in the observation group saw a significant reduction in their depression and anxiety scores along with increased life satisfaction, psychological resilience, and sleep quality, thereby indicating that combining big data analysis of physical activity behavior with targeted psychological counseling can regulate neurotransmitter secretion through exercise, alleviate negative emotions, and enhance individual psychological resilience. Meanwhile, the control group, which did not receive any intervention, showed no significant changes in any of the indicators, further highlighting the effectiveness and unique advantages of data-driven intervention programs in improving physical activity and mental health.

However, this study still has certain limitations. In terms of data collection, although wearable devices were used to gather exercise data, avoiding data bias remained a challenge. On the one hand, wearable devices can introduce measurement errors. For example, step counts may be inflated due to non-exercise behaviors such as arm swinging, while heart rate monitoring accuracy may be reduced in complex exercise scenarios. On the other hand, mental health assessments rely on self-report questionnaires, which can be influenced by individual subjective perceptions, emotional states, and social expectations, thus potentially distorting the data and reducing the precision of the research findings. Additionally, this study only covered individuals aged 18–60 years and excluded special groups, such as adolescents and the elderly. Individuals from various age groups show significant differences in their exercise capacity, psychological traits, and health needs, thus limiting the generalizability of the research conclusions. Future studies should expand the sample size to enhance representativeness.

Based on the above conclusions, the following suggestions for improvement are proposed. In terms of practical application, big-data-based sports behavior analysis and mental health intervention programs should be promoted in communities, schools, and enterprises. To enhance the feasibility of community implementation, the increasing penetration of smart wearables (e.g., Apple Watch) and mature network infrastructure in communities should be leveraged. Machine learning models, such as random forest and neural networks, introduces the following core technical advantages: ① Precise profiling: These models analyze multi-dimensional data (e.g., exercise, heart rate, and sleep) to build individual health models and establish correlations between behavioral patterns and mental states (e.g., elevated anxiety risk after prolonged sitting), thereby offering early warning and personalized interventions. ② Dynamic adaptation:

Real-time data analysis auto-adjusts exercise (e.g., lowering outdoor activity thresholds in hot summers) and psychological strategies (e.g., playing relaxing music when facing high stress), thereby ensuring continuous “tailored-to-individual” optimization. ③ Resource integration: Medical, fitness, and psychological data interfaces should be integrated. These models fuse physical exam reports, exercise courses, and counseling records to create cross-scenario health plans (e.g., “exercise + diet + psychological intervention” for diabetes patients). Communities can collaborate with tech companies to build big data health management platforms that provide residents with personalized exercise and psychological intervention services [23]. More precise and convenient smart wearable devices and big data analysis platforms should also be developed to enhance the accuracy and real-time nature of data collection. Resources from multiple fields, such as healthcare, fitness, and psychology, should be integrated to establish interdisciplinary collaboration mechanisms [24]. For example, medical institutions can provide professional psychological assessments, while fitness centers can design scientific exercise courses, thereby jointly refining the big data intervention program [25]. In subsequent research, the sample size can be expanded to include different regions, cultural backgrounds, and occupational groups to further reinforce the universality of the intervention program. Specialized studies should also be conducted for specific populations, such as adolescents, the elderly, and patients with chronic diseases, to develop more targeted intervention strategies.

Author Contributions

Yulin Zhou designed, collected and analyzed the data, and drafted the manuscript. Yulin Zhou conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Yulin Zhou participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

Conflict of Interest

The author declares no conflict of interest.

Funding

This research received no external funding.

Ethics Approval and Consent to Participate

This survey was conducted in compliance with [Ethics Committee of Henan Forestry Vocational College] (HFVC-045). Participants were informed of the study's purpose and data usage prior to participation, and responses were collected anonymously. No personally identifiable information was stored.

Availability of Data and Materials

The datasets used and/or analysed during the current study were available from the corresponding author on reasonable request.

Acknowledgements

Not applicable.

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