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# Network intervention analysis to assess the trajectory of change and intervention effects associated with the use of self-control training for ego depletion aftereffects

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## Abstract

**Purpose** The purpose of this study was to use the advanced technique of Network Intervention Analysis (NIA) to investigate the trajectory of symptom change associated with the effects of self-control training on youth university students' chronic ego depletion aftereffects.

**Methods** The nine nodes of chronic ego depletion aftereffects and integrated self-control training were taken as nodes in the network and analyzed using NIA. Networks were computed at the baseline, at the end of treatment, at 1-, 3-, 6-, 9- and 12-month follow up. 62 samples were recruited from universities and randomly divided into two groups. The sample ranged in age from 18 to 25 years and included both males and females.

**Results** Self-control training interventions directly improved the states of low self-efficacy, low adherence, and work burnout, as well as indirectly alleviated fatigue, emotional regulation disorders, and other issues. Follow-up surveys showed that the intervention not only had immediate effects but also had long-term effects.

**Conclusion** These findings indicate that self-control training has a direct intervention effect on low self-efficacy, low adherence, and work burnout of youth university students' ego depletion aftereffects. This study is the first application of NIA in abnormal psychological state intervention research outside the field of mental disorder treatment. NIA is a promising method to evaluate the trajectories of intervention change and the direct and indirect effects of training interventions.


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**Keywords** Network intervention analysis (NIA), Self-control training, Youth university students, Ego depletion aftereffects, Intervention effects

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## Introduction

Self-control is the ability to guide and manage one's own thoughts, emotions, and behavior [1]. It can help people achieve their goals, inhibit impulses, and correct their behavior direction in response to feedback. However, this ability manifests differently in different situations. After continuous high-intensity self-control tasks, people's self-control abilities will decrease, resulting in ego depletion aftereffects [2]. This phenomenon has attracted extensive attention in the field of psychology and has become one of the main factors affecting individual life, learning, and work efficiency [3]. Ego depletion manifests as the consumption of resources, and its most direct manifestation is fatigue generated after completing consecutive self-control tasks [4]. Ego depletion not only affects the efficiency of working and learning but also influences the development of personal willpower and self-control [5].

Ego depletion is a psychological phenomenon where individuals experience a temporary decline in their capability to exert self-control after engaging in tasks that require self-regulation or self-control over an extended period [6]. The self-control strength model explains self-control as a finite and renewable resource, wherein prolonged engagement in tasks requiring self-regulation diminishes the level of this resource, restricting its application in other tasks [5]. In today's world, there is a considerable amount of ego depletion [7]. With the presence of choices, regulations, and desires, individuals are continuously required to exercise self-control [1], including resistance to temptations [8], change of habits [9]and suppression of instincts [10]. This ubiquity of demands leads to the inevitability of ego depletion [11]. The degree of ego depletion experienced will influence individuals' capability to maintain optimal performance and psychological well-being in their daily lives [7].

In the daily routine, university students require a substantial amount of self-control, such as completing monotonous tasks [12], handling last-minute urgent notices [13], and regulating positive or negative emotions [14]. Once psychological energy is excessively depleted due to extensive self-control, these university students may enter a state of ego depletion [15], hindering normal emotional expression [16], leading to adverse social behaviors [17], underestimation of their abilities [18], decline in working memory [19], inability to concentrate [20], loss of motivation for learning [21], abandonment of fitness plans [20], and even involvement in exam cheating [17], rule violations [22], and aggressive behaviors [23].

To ensure good performance in their daily lives, studies, and work, university students should adjust and control their levels of self-control according to their individual circumstances to avoid the detrimental effects of ego depletion. However, it is evident that students in universities experience tremendous self-control pressures. For instance, adapting to university management may lead to manifestations of ego depletion [24]; resisting various temptations outside campus requires significant psychological resilience [6]; completing tight and demanding tasks assigned by superiors may result in ego depletion [12]; and even maintaining constant politeness, and presenting an ideal image to others in daily life can consume psychological resources [25]. Therefore, to enable university students to effectively combat ego depletion, alleviate its adverse effects, and enhance their academic and personal performance, it is paramount to seek appropriate intervention methods.

Many studies have explored the effects of self-control training on ego depletion aftereffects and have found that the engagement of self-control training can improve individuals' self-control ability and resistance to ego depletion aftereffects [26]. For example, measures such as posture adjustment [15], physical exercise [27], monitoring dietary habits [28], inhibition control task training [29], and emotion regulation training [30] can all improve the self-control capacities of individuals. However, due to the complex interrelationships among the different components of ego depletion aftereffects, these studies have assumed a simple causal relationship to investigate the effects of self-control training on ego depletion aftereffects, ignoring the complex relationships among these factors and not conducting a comprehensive investigation into the underlying intervention mechanisms.

In recent years, Network analysis (NA), with its ability to uncover underlying patterns of mental health and psychopathology, has become a hot research area [31]. A growing number of studies have used NA to explore psychological structures such as personality [32], anxiety [33], depression [34], post-traumatic stress disorder [35], Self-worth [36], and decision-making [37].From the perspective of network analysis, the occurrence of mental disorders is a sudden phenomenon caused by a causal interaction between different symptom elements [38]. The NA is data-driven and does not rely on prior assumptions involving variables for mathematical analysis of relationships among variables [39]. Compared with traditional models, network analysis offers several main methodological advantages in the current research context. (1) Theory. NA provides a new way to conceptualize psychological constructs, assuming that psychological constructs are a complex system phenomenon caused by the interaction of their components [40]. Typically, the psychological network uses nodes to represent observed variables such as symptoms, behaviors, and feelings, and reveals connections between them through connections between nodes [41]. (2) Visualization. Network analysis provides a valuable tool for visualizing patterns of statistical association among complex and interrelated psychological data. By examining the network structure, researchers can gain direct insights into the degree of correlation between different nodes, identify key intermediary nodes, and unravel other relationships within the network [42]. (3) Statistics. When constructing mental networks, researchers usually adopt the method of partial correlation network model combined with regularization techniques [31]. These correlations, derived following controlling for other variables and using statistical regularization techniques, signify more refined, concise, and interpretable relationships within multivariate data, consequently enhancing generalizability to novel samples [43].

Network Intervention Analysis (NIA) is a method developed by Blanken et al. (2019) [44]based on network theory specifically for studying intervention mechanisms. It involves evaluating the intervention by incorporating the intervention condition as a binary variable (0=control group, 1=intervention group) into the symptom network. In randomized controlled trials, since the assignment of the intervention condition occurs before the implementation of the intervention, changes in symptoms cannot affect the intervention condition [44]. Therefore, all links between the intervention condition and symptoms represent the effect of the intervention [45]. As mentioned above, network theory suggests that psychological structures are a complex system phenomenon caused by the interaction of their components. This may facilitate a shift in research focus towards the components of psychological constructs. Furthermore, considering that the effects of treatments for mental disorders might be symptom-specific [46]. Thus, employing symptom networks to assess mental health interventions could potentially expand the understanding on treatment effects by highlighting individual symptoms and their connections [47].Traditional NIA usually uses LASSO regularization algorithm [48] to ensure high specificity, where small intervention effects and weak associations are more likely to go unnoticed. The absence of direct edges between symptom nodes and intervention condition nodes should not be simply interpreted as having no effect, but rather may indicate the presence of indirect intervention effects. Direct edges between intervention conditions and symptom nodes represent direct intervention effects, reflecting stronger intervention effects [46]. The purpose of this study was to verify whether the integrated self-control training measures developed to effectively reduce ego depletion levels, considering the three core nodes (fatigue, low self-efficacy, and emotional regulation disorders) identified from the symptom network analysis of ego depletion aftereffects in youth university students [49], and to explore changes in ego depletion aftereffects related to intervention.

To achieve this, this study used Network Intervention Analysis (NIA) to explore the effects of self-control training on ego depletion aftereffects in youth university students, with a focus on the interactions among the various components in the symptom network.

## Method

### Participants

Select participants from a university in Xi'an, participants need to be in a state of ego depletion and the inclusion criteria for participants are: (1) at least one dimension of Ego Depletion Aftereffects Scale (EDA-S) [50] scores is higher than 2; (2) no significant emotional fluctuations or major family changes in the past month; (3) willing to participate and able to complete all experimental tasks. The exclusion criteria are: (1) all dimensions of EDA-S scores are no higher than 2; (2) significant emotional fluctuations or major family changes in the past month; (3) unwilling to participate in the experiment or unable to complete all experimental tasks. Sample size calculation: GPower 3.1.9.2 software was used for sample size estimation, with a significance level of 5%, an effect size of 0.25, and a power of 0.95. The calculated total sample size is 36. 62 participants who met the inclusion criteria were selected, and the sample size is sufficient. Then, a random software was used to randomly assign participants to the training intervention group and the blank control group. There were no significant differences in major demographic variables such as age and gender between the two groups, and in the scores of each dimension of ego depletion after-effects in the pre-test. The ethics of this study were approved by the university institutional review board, and all participants read and provided informed consent before the study began.

### Ego depletion aftereffects scale

We used the Ego Depletion Aftereffects Scale (EDA-S) compiled by Yicheng Tang and colleagues in 2016: This scale consists of 38 items scored on a 5-point scale, with higher scores indicating greater levels of ego depletion [50]. The α coefficients for each factor range from 0.73 to 0.89 [49]. The EDA-S can assess youths' level of ego depletion [50]. The dimensions are described as follows: (1) Somatic distress α=0.887, items 1~8, 40 points, for example: "I feel numb or tingling"; (2) Fatigue α=0.886, items 9~14, 30 points, for example: "I feel like I need more rest"; (3) Low processing fluency α=0.869, items 15~19, 25 points, for example: "I've been thinking harder than ever lately"; (4) Work burnout α=0.889, items 20~22, 15 points, for example: "I doubt the meaning of study or work"; (5) Working memory loss α=0.841, items 23~26, 20 points, for example: "I often forget where I have lost my clothes, glasses, shoes, toys, books, pencils, etc."; (6) Emotional regulation disorder α=0.851, items 27~29, 15 points, for example: "I find it harder to control my temper than before"; (7) Social withdrawal α=0.764, items 30 ~ 32, 15 points, for example: "I find it hard to be polite to others all the time"; (8) Low adherence $\alpha=0.727$, items 33 ~ 35, 15 points, for example: "I find it hard to stick to healthy habits"; (9) Low self-efficacy $\alpha=0.860$, items 36 ~ 38, 15 points, for example: "I feel that I can not effectively solve the problems in my study or work."

### Intervention

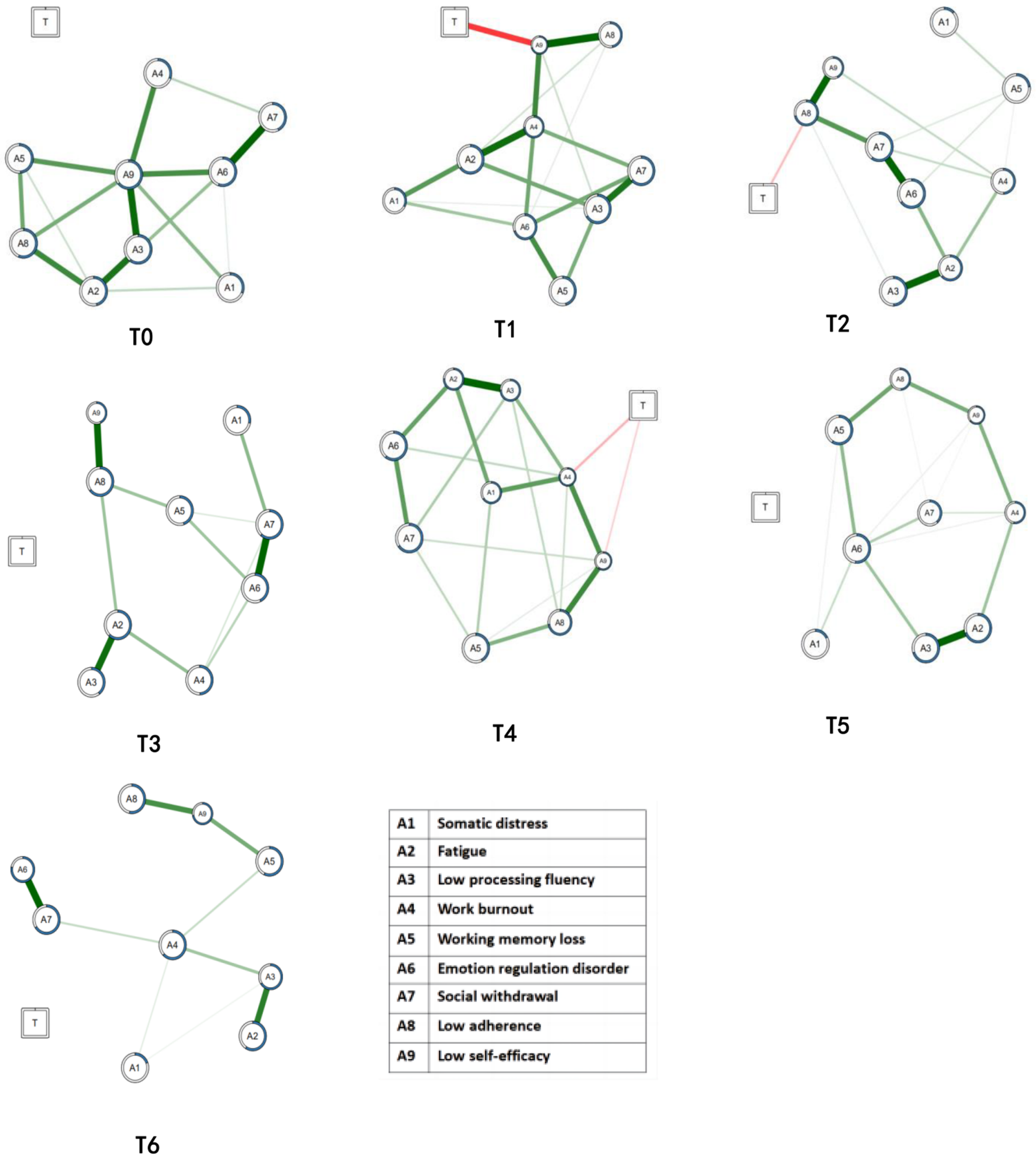
The intervention group accessed a digital platform, downloaded materials and instructions for the three training tasks, and completed the training on their own in their dormitory or in a quiet and independent laboratory with video recording. The three tasks, Go/Nogo inhibition task [29], emotional film task [5], and plank support task [30], were combined as an integrated self-control training task. The training lasted for 3 weeks, with 2 training sessions per week, and each task lasted for about 10 min, with a complete training session taking about 30 min. The control group did not receive any training. Self-report measures were collected using an online questionnaire platform (www.wjx.cn) at baseline before the training, at the end of the 3-week training, and at 7 follow-up time points of 1, 3, 6, 9, and 12 months after the training ended.

### Network estimation

The intervention condition is included in the ego depletion aftereffect symptom network, and the EDA-S nine-dimensional scores are treated as continuous variables. The intervention is treated as a binary variable (0 = control group, 1 = intervention group) and is included in the analysis as a network node. The network model is constructed, and the network analysis is completed using R 4.2.2 and R packages mgm [51] and qgraph [52]. We used the NIA method to estimate the regularized network at the baseline, immediate post-training, and 1, 3, 6, 9, and 12 months after training. In addition to all the dimensions of the EDA-S, a binary processing "treatment" allocation variable (represented by a square) [44] is also included. This process not only allows us to track the order of changes in the severity of individual symptoms caused by training but also distinguishes specific symptoms that are most directly affected by training and those that are indirectly affected at each time point. In addition, NIA also reveals the sequence of development of the association network structure induced by training intervention by estimating the proportion of variance explained by other symptoms in the network for each symptom (called predictability) [53]. We also examined the accuracy and stability of the network. We used extended Bayesian information criteria (EBIC) with a gamma hyperparameter of 0.25 to estimate the regularized network. The results showed differences in symptom severity improvement in the network, and the size of the nodes in the network was correlated with the difference in symptom severity between the two groups: the node size reflected the intervention effect. To reflect the intervention effect (difference between the control group and the experimental group) in the network model diagram, we associated the node size representing the data of each dimension with the score difference between the control and intervention groups. If the intervention group's score was significantly higher than the control group's score, the node size would increase, and if the intervention group's score was significantly lower than the control group's score, the node size would decrease. Because the score range of different dimensions is different, it is unreasonable to determine node size based solely on score differences. At the same time, considering that the method used for the difference test is an independent sample t-test, the size of the node is divided into six levels based on the significance of the t-test difference, which are three levels of positive difference ($P<0.05$, $P<0.01$, $P<0.001$) and three levels of negative difference ($P<0.05$, $P<0.01$, $P<0.001$). Predictability, which is the proportion of the variance in the node explained by all other nodes in the network [54], is calculated and displayed as the proportion of cycles surrounding each node at each time period (baseline, post-test, 1st month, 3rd month, 6th month, 9th month, and 12th month). The variance of symptoms is calculated at each evaluation and associated with predictability to examine whether the change in predictability is related to the increase or decrease in variance observed during the treatment process. The lack of significant correlation can be explained as the key factor in changing the network structure during training. The difference in edge weights in the network is evaluated using the mgm package (with a bootstrap sample size of 1000) [55].

## Results

The after-effect dimensions of the EDA-S were taken as nodes, and a network was constructed by adding training intervention conditions (0 = control group, 1 = intervention group). The results are shown in Fig. 1, which displays the trajectory of pre-test (baseline) and symptom-specific training effects within one year. The training intervention node (T) is directly connected to the low self-efficacy node (A9), but has no direct association with the fatigue (A2) and emotion regulation disorder (A6) nodes. Direct effects of training on variables were observed at the post-test, 1-month, and 6-month follow-up, specifically negative effects on low self-efficacy (A9), low adherence (A8), and work burnout (A4).




| | |
|---|---|
| A1 | Somatic distress |
| A2 | Fatigue |
| A3 | Low processing fluency |
| A4 | Work burnout |
| A5 | Working memory loss |
| A6 | Emotion regulation disorder |
| A7 | Social withdrawal |
| A8 | Low adherence |
| A9 | Low self-efficacy |

**Fig. 1** *Note* T0 represents baseline assessment before training, **T1** represents immediate post-training assessment, and **T2**, **T3**, **T4**, **T5**, **T6** represent assessments at 1, 3, 6, 9, and 12 months after training, respectively. Nodes represent training interventions and EDA-S dimensions: self-control training (T), somatic distress (A1), fatigue (A2), low processing fluency (A3), work burnout (A4), working memory loss (A5), emotion regulation disorder (A6), social withdrawal (A7), low adherence (A8), and low self-efficacy (A9). The thickness of the edges represents the degree of correlation. Green edges indicate positive correlations, while red edges indicate negative correlations. The circle surrounding each node describes its predictability. Red edges between the binary intervention (T, square) nodes and symptom nodes indicate that the intervention group scores lower than the control group. Node size reflects the relative difference in intervention-induced changes since baseline, with smaller sizes indicating greater intervention effects

The maximum differential effect of the training intervention (indicated by node size) was on low self-efficacy (A9), which showed differential effects at all six time points within 12 months after the end of training. The predictability, or the amount of variance explained by other symptoms in the network, decreased from an average of 71% at baseline to 62% after 12 months. The variance of all variables in the network did not show a significant difference over time, and the correlation between observed variance and predictability was not significant at each assessment ($P > 0.05$). Therefore, changes in predictability were not driven by changes in observed variance of all variables.

At the baseline assessment time point (T0) before the intervention, there was no correlation between the intervention and symptoms, and the training intervention node (T) had no connection with all symptom nodes. The symptom nodes were of equal size, indicating that no intervention effects had appeared, and there was no significant difference between the intervention group and the control group. The smaller the node, the greater the improvement due to the intervention.

At the post-training assessment time point (T1), the most significant change was that the "T" node was strongly connected to the low self-efficacy (A9) node, and the nodes that decreased in size were somatic distress (A1), work burnout (A4), emotion regulation disorder (A6), low adherence (A8), and low self-efficacy (A9).

At the one-month follow-up assessment time point after the end of training (T2), the "T" node was directly connected to the low adherence (A8) node, and the nodes that decreased in size were fatigue (A2), work burnout (A4), low adherence (A8), and low self-efficacy (A9).

At the three-month follow-up assessment time point after the end of training (T3), the "T" node had no direct connection to any node, and the node that decreased in size was low self-efficacy (A9).

At the six-month follow-up assessment time point after the end of training (T4), the "T" node was directly connected to both the low self-efficacy (A9) and the work burout (A4) nodes, and the nodes that decreased in size were somatic distress (A1), fatigue (A2), low processing fluency (A3), work burnout (A4), low adherence (A8), and low self-efficacy (A9).

At the nine-month follow-up assessment time point after the end of training (T5), the "T" node had no direct connection to any node, and the nodes that decreased in size were work burnout (A4), social withdrawal (A7), low adherence (A8), and low self-efficacy (A9).

At the twelve-month follow-up assessment time point after the end of training (T6), the "T" node had no direct connection to any node, and the nodes that decreased in size were low processing fluency (A3), emotion regulation disorder (A6), and low self-efficacy (A9).

## Discussion

Due to the fact that the allocation of the "treatment" variable in training occurred before randomization, the training variable would affect the symptom variable, but the symptom variable would not affect the training variable in return. Therefore, the edge between the treatment node and the symptom can determine the symptoms directly affected by training. The impact of training on each symptom relative to the changes observed in the control group is represented by the size changes of the nodes.

Firstly, the edge between the training variable and the symptom variable shows the direct impact of training on low self-efficacy (A9), low adherence (A8), and work burnout (A4). This effect began immediately after training and continued to be effective within 6 months after intervention completion (except at T3 time). Low self-efficacy is one of the cores of the ego depletion aftereffects network of youth university students [49]. According to network theory, if the intervention can directly affect the core of the symptom network, it may break or weaken the vicious circle of the network, thereby reducing abnormal psychological states.

Secondly, NIA enables us to observe how the intervention activates changes in the associations between symptoms. Sequential development indicates that the training primarily and most consistently improves low self-efficacy (A9), from T1 to T6, followed by low adherence (A8) and work burnout (A4) (both from T1 to T2, and then T4 to T5). Only after the first month following the end of training, did fatigue (A2) improve (T2 and T4), indicating that the intervention first affected low self-efficacy (A9), and then affected fatigue (A2).

The NIA results also demonstrated that the direct impact of the training on these specific symptoms subsequently spread through the network via their connections to other symptoms. For example, one of the strongest training effects was on low adherence (A8), even though only one training at T2 directly impacted low adherence (A8). In addition, we found that working memory loss (A5) was the only node that consistently did not show significant changes at all assessment time points. A recently published result from our study [49] on the symptom network of youth university students with ego depletion found that the working memory loss (A5) node had the lowest predictability in the ego depletion symptom network, confirming that it was difficult to be influenced by other nodes in the network. We also speculated that the later training effect may become ineffective due to the temporary high risk of youth university students, and we found that most of raining effects suddenly disappeared at T3. Considering that T3 is the final exam period, we believed that the reason may be that the demand for self-control during exam preparation and after the exam is significantly higher than usual, and the ceiling effect of ego depletion aftereffects is reached, and the training effect cannot be reflected. Therefore, for special time points such as final exams, it is necessary to consider adjusting the exam schedule, providing more rest time and specialized psychological interventions.

For each symptom, we also checked whether the amount of variance explained by other symptoms (i.e., predictability) during the intervention tracking period changed, with the average decreasing from 71% at baseline to 62% after 12 months. However, the variance of all variables included in the network showed no significant differences. During the intervention, there was no increase or decrease in the predictability caused by the increase or decrease in the symptom difference system, indicating that the change in predictability can be primarily explained by the intervention.

If interventions can directly affect the core of symptom networks, they may disrupt or weaken the vicious circle within the network, thus alleviating mental disorders or abnormal psychological states [56]. In this study, the mechanisms through which training interventions influence the core elements of ego depletion mainly fall into two categories. On one hand, training interventions operate through both direct and indirect effects on core nodes of symptoms, such as nodes representing low self-efficacy. It can be seen from both the symptom network [49] and the intervention network that the primary core node affected by training interventions is low self-efficacy. Increasing self-efficacy directly contributes to mitigating the aftereffects of ego depletion. Furthermore, low self-efficacy can also indirectly influence other nodes through network transmission [49], thereby reducing the aftereffects of ego depletion. In a previous study, we found that all nodes of the ego depletion symptom network were positively correlated, and the edge results indicated low self-efficacy and work burnout, as well as low self-efficacy and low adherence are closely related [49]. The strong partial correlation suggests that the two connected nodes may have high co-occurrence and easily influence each other [53]. For example, in post-training assessments, low self-efficacy can impact strong neighboring nodes like work burnout and low adherence, thereby affecting the entire symptom network of ego depletion aftereffects. We observed improvements in two other core symptom nodes (fatigue and emotion regulation disorders) during the follow-up assessments, but these changes are more likely to be caused by the indirect influence of low self-efficacy nodes. On the other hand, training interventions act by transmitting the impact on the aftereffects of ego depletion through improving the core node of impulsivity trait (distractibility). At the sixth month after training, the low self-efficacy node once again showed a direct effect of the training intervention. It is possible that the intervention initially affects the distractibility node in the impulsivity trait, and then the improvement in the distractibility node effectively increases self-efficacy by transmitting powerful influences through "bridges". In summary, self-control training interventions can influence the core of ego depletion networks from multiple perspectives, weakening the vicious cycle within ego depletion and effectively mitigating ego depletion.

The limitations of this study are, firstly, although longitudinal data were collected, the time intervals were too long to capture the changing characteristics of ego depletion aftereffects in shorter periods (such as monthly, weekly, or daily intervals), and it may be worthwhile to consider combining empirical sampling method (ESM) [57] in future studies. As an intensive longitudinal data collection method, ESM repeatedly measures real-life symptoms with the help of devices such as computers and smartphones, and the data collection is closer to the nature of psychological symptoms [49]. Secondly, we only analyzed the impact of training on ego depletion aftereffects, and a more in-depth study could include impulsivity traits, academic performance, BMI, and other factors. As suggested in a previous Systematic Review (encompassing network analysis, mental health problems, and intervention studies), incorporating potentially relevant variables into the network alongside symptoms capitalizes on the capability of networks to depict connections among various variables, potentially enhancing insights into treatment effects derived from network analysis [58]. Finally, the effects of this study are limited to the between-subject effects at a group level, and may not happen in precisely the same manner within an individual.

## Conclusions

This study used the Network Intervention Analysis (NIA) method to find that integrated self-control training directly improved the states of low self-efficacy, low adherence, and work burnout, while being more likely to indirectly alleviate the states of fatigue, emotional regulation disorders, etc., with immediate and long-term intervention effects. However, more targeted interventions are needed to improve other core manifestations of ego depletion aftereffects in youth university students, such as using relaxation techniques to alleviate fatigue and using necessary medication to treat emotional regulation disorders (such as anxiety and depression).

NIA, as an innovative method to assess the trajectory of ego depletion behavior changes in youth university students and the direct and indirect effects of training interventions, can provide important guidance for the development of future training interventions and offer new ideas for the intervention evaluation of other abnormal psychological or sub-healthy states in youth university students.

**Abbreviations**

| | |
|---|---|
| NIA | Network Intervention Analysis |
| NA | Network Analysis |
| LASSO | Least Absolute Shrinkage and Selection Operator |
| EDA-S | Ego Depletion Aftereffects Scale |
| EBIC | Extended Bayesian Information Criteria |
| ESM | Empirical Sampling Method |
| BMI | Body Mass Index |

## Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s40359-024-02326-z.

Supplementary Material 1

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**Author contributions**
JY, XZ, and XL conceived and designed the study. JY, WX and XZ collected the data. JY and XZ analyzed the data. JY, XZ, LR, RW and XL contributed reagents, materials, and analysis tools. JY, XZ, WX and XL wrote the manuscript. All authors contributed to the article and approved the submitted version.

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**Data availability**
The original contributions presented in the study are included in the article/Supplementary material, further inquiries can be directed to the corresponding authors.

## Declarations

**Ethics approval and consent to participate**
The studies involving human participants were reviewed and approved by the Independent Ethics Committee of the First Affiliated Hospital of the Fourth Military Medical University (No. KY20202063-F-2). The participants provided their written informed consent to participate in this study. All experiments were performed in accordance with relevant guidelines and regulations.

**Consent for publication**
Not applicable.

**Competing interests**
The authors declare no competing interests.

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