The Design and Implementation of an Intelligent Sports Training System for College Students' Mental Health Education

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Abstract

Unconsciously, mobile Internet information influences college students' sports behavior and awareness, although the exact consequences have not been widely studied. The majority of the extant research focuses on behavioral science and sports communication. Using past research as a foundation, this study investigates the impact of mobile Internet on college students' sports behavior and awareness. In particular, a static structural analysis was performed on an intervention event network for the effect of mobile Internet on college students' sports behavior and awareness. Then, using system event analysis, a well-established method in complex system research, the interaction link between distinct intervention events in the network was investigated in depth, and the composite degree of effect between them was calculated. The core logic and action mechanism of the event-based hierarchy model were then revealed using the integrated fuzzy-interpretative structural model. Finally, experiments confirmed that the proposed paradigm was successful.

Keywords: Mobile Internet, college students, sports behavior, sports awareness, intervention model

1. Introduction

One of the biggest problems with the mental health care system is lack of resources available to college students, especially those living on their own or those who are not affiliated with school. This can lead to a greater number of suicides and other mental health problem cases. College students may be particularly vulnerable due to economic issues, high alcohol consumption, and as a result high levels of stress. Many universities have instituted peer hotline services that are staffed by student volunteers. These hotlines may provide general information on mental health issues, but do not offer the level of service needed to help a person actually get better. An intelligent sports training system (IST) is designed to track and predict patterns in order to increase efficiency and reduce costs (Darmody & Bendis, 2021). This system is designed with a built-in knowledge mining process that uses AI algorithms based on data mining methods which will extract useful pieces of information from large amounts of unstructured data. An auto associative neural network is used to produce an auto associative feature map after the patterns in the learning data are analyzed. The auto associative feature map allows the IST to perform more quickly, efficiently, and accurately than other forms of AI. The system works by identifying specific areas of improvement in an individual and using specific types of cues to improve their mental health. For example, if an individual is experiencing anxiety issues, the IST would identify what stresses them out in their daily life and it will give them cues to help them handle these problems. Therefore, the system will learn from its mistakes as it goes through each training session. The IST uses a three-layered neural network, which consists of a two-layer feed forward layer and one hidden layer. The inputs to the feed forward layer are from the output of the auto associative feature map and the hidden layer is used to transform input values into output values (Ramirez-Ubillus et al., 2020). The feed forward neural networks are equipped with general purpose machine learning algorithms that provide a training set by showing data captured from each individual's health assessment. The training data is then refined and optimized to create an optimal solution for each individual. Each session will start with a baseline test where this machine learning model is trained and then tested on the same subject. The training data will be used to train the algorithm, and the testing data will be used to test the performance of the algorithm. The AI is not perfect, and there are many potentials for improvement based on its efficiency (Saad Fricke & Zhukov, 2021; Yang, 2021).

The system uses a combination of prediction and scenario analysis that allows it to provide a level of service that cannot be attained by other forms of AI. Prediction involves predicting future actions based on past actions which is useful in terms of planning for future procedures. Scenario analysis using this system will make it possible for college students to receive help at any time since it can make predictions about a person's behaviors at any given time. Technology is beginning to play a greater role than ever in our daily lives. Too often, however, it is used as the means through which we do not live life - but rather just buy and consume what we want or need. The design and implementation of an intelligent sports training system for

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college students' mental health education examines the current state of gaming addiction and highlights the potential benefits of applying technology more effectively to enhance students' understanding of their mental wellness in relation to physical activity. This opens up a new world of possibilities by giving users a less passive experience with many perks such as "lifetime" access, an interpersonal design with key demographic groupings, and individualized feedback scores (Wang, 2020; Zhang, 2020).
- A new paradigm of sports training and mental health education emerges by following the example set by game designers and developers. The proposed system is an interactive, gamified experience that allows users to learn about themselves and their peers while experiencing a deep emotional bond with their in-game environment. The result is a more personalized, effective mental health education that evolves according to the individual user's performance levels (Fricke, 2017; Xu, Liang, & Ji, 2020).
- By integrating technology more effectively than ever before, this project explored the impact of "gamification" on student mental wellness and identified techniques for incorporating design elements (e.g., aesthetics) that could potentially provide students with a unique experience through which they can improve their mental fitness. Mobile Internet enables college students to acquire various information easily and rapidly (Aziz, Setyawan, & Saddhono, 2021; Chuang, Chou, & Chen, 2005; Dong, 2021; Kim & Kim, 2019; Li & Li, 2022; Li & Fan, 2021; Li, 2021; Lin, Jiang, & Wang, 2013; Liu, Lin, & Lee, 2011; Liu, Li, & Du, 2021; Liu & Li, 2013; Liu et al., 2012; Lu et al., 2019). The proliferation of intelligent mobile terminals further boosts the application of mobile Internet in the dissemination of sports knowledge, sports games, and sports news, as well as in physical exercise services (Luo & He, 2021; Min, 2017). The information of mobile Internet affects the sports behavior and sports awareness of college students unconsciously (Neha, Sidiq, & Zaman, 2021; Sun et al., 2018). To guide college students to correctly receive sports information from mobile Internet, it is necessary to deeply explore the college students' utilization of sports information in mobile Internet, and examine the influence of this information over the behavior and awareness of college students. The relevant results would promote the healthy development of mobile Internet, and improve the sports quality of college students (Reaume, 2021).

The development of digital technology is improving the lifestyle and behavior of ordinary people around the world. In recent years, some scholars investigated the penetration of network-based sports applications in students' entertainment activities. (Sun & Li, 2021; Yao, Wu, & Wu, 2012) Reviewed the literature on that penetration through a systematic topic analysis. Using a specific data analysis model, the quantitative information of ten selected studies were subjected to a strict topic analysis in five steps: compilation, decomposition, reorganization, interpretation, and summary. The results show that systematic topic analysis effectively encourage students to participate more in low-intensity sports. Qiu (2017); Zhang and Hu (2020) explored the attitude, motivation, constraints, and satisfaction of college students in Taiwan, and then clarified the participation behavior patterns of sports and leisure, as well as the relationship between these patterns. Next, a regression analysis was performed on the satisfaction with sports and leisure activities on campus. The results suggest that the participation in sports activities promotes the satisfaction, while the participation in leisure activities has the strongest, most significant, and most direct effect on the satisfaction. With the aid of computer technology, Wu (2021) discussed the changes in lifelong sports awareness of 500 students from three colleges in southeastern China's Fujian Province after participating in community interaction, and reflected the positive impacts of community interaction on lifelong sports awareness of college students (Corrêa et al., 2020; Xiaodong & Weidong, 2021). Through literature review and field surveys, Wu (2022) studied the physical exercise state and awareness of college students, in the context of the physical education (PE) course reform of Chinese colleges, and tried various means to help college students experience the function and fun of physical fitness. In this way, they managed to bolster the motivation and interest of college students in sports participation, stimulate their lifelong sports awareness, and encourage them to take part in sports activities more actively.

Chinese scholars rarely explored how the sports information of mobile Internet affects the sports behavior and sports awareness of college students. Foreign scholars mainly focused on behavioral science and sports communication. Drawing on the previous research, this paper comprehensively investigates the influence of mobile Internet over the sports behavior and sports awareness of college students (Xie, Zhang, & Liu, 2021). Section 2 establishes an intervention event network for the influence of mobile Internet over the sports behavior and sports awareness of college students, and carries out a static structural analysis, including node features, node centrality, and network centrality. Section 3 relies on system event analysis, a mature tool in complex system research, to deeply examine the interactive relationship between different intervention events in the network, and quantify the composite degree of influence between them. Section 4 adopts the integrated fuzzy-interpretative structural model to reveal the internal logic and action mechanism of event-based hierarchy model. Finally, the effectiveness of our model was tested through experiments (Sánchez et al., 2019; Zheng & Chen, 2021).

2. Network Construction and Static Structural Analysis

2.1 Network construction

This paper sets up an intervention event network for the influence of mobile Internet over the sports behavior and sports awareness of college students, which includes nine interventions in two categories, namely, implicit intervention I_1 and explicit intervention I_2.

Implicit intervention includes the intervention of mobile Internet on college students' sports value I_{11}, attitude to physical exercise I_{12}, sports interest I_{13}, and motive of sports participation I_{14}.

Explicit intervention includes the intervention of mobile Internet on college students' physical exercise state I_{21}, acquisition method of sports information I_{22}, state of sports consumption value I_{23}, and state of idol worship I_{24}.

Specifically, sports value I_{11} includes the intervention on college students' educational growth I_{111}, body fitness I_{112}, interpersonal relationship I_{113}, spirit I_{114}, leisure and entertainment I_{115}, social economy I_{116}, social stability I_{117}, and patriotism I_{118}.

Attitude to physical exercise I_{12} includes the intervention on college students' cognitive attitude I_{121}, emotional experience I_{122}, behavioral intention I_{123}, and behavior control I_{124}.

Sports interest I_{13} includes the intervention on college students' attitudes like strongly uninterested I_{131}, slightly uninterested I_{132}, neutral I_{133}, slightly interested I_{134}, and strongly interested I_{135}.

Motive of sports participation I_{14} includes the intervention on college students' school performance I_{141}, interpersonal communication I_{142}, entertainment and relaxation I_{143}, bodybuilding I_{144}, and hobbies and interests I_{145}.

Physical exercise state I_{21} includes the intervention on college students' time of each physical exercise I_{211}, frequency of physical exercises I_{212}, intensity of physical exercise I_{213}, venue selection of physical exercise I_{214}, items of physical exercise I_{215}, and organizational form of physical exercise I_{216}.

Acquisition method of sports information I_{22} includes the intervention on college students' interaction with new media I_{221}, we media I_{222}, and online videos I_{223}.

State of sports consumption value I_{23} includes the intervention on college students' sports consumption level I_{231}, and sports consumption items I_{232}.

State of idol worship I_{24} includes the intervention on college students' idol worship I_{241} and lack of idol worship I_{242}.

Figure 1 shows the action mechanism of the intervention events. Without considering the indirect effects between the intervention events, this paper constructs the intervention event network solely based on the direct effects between these events.

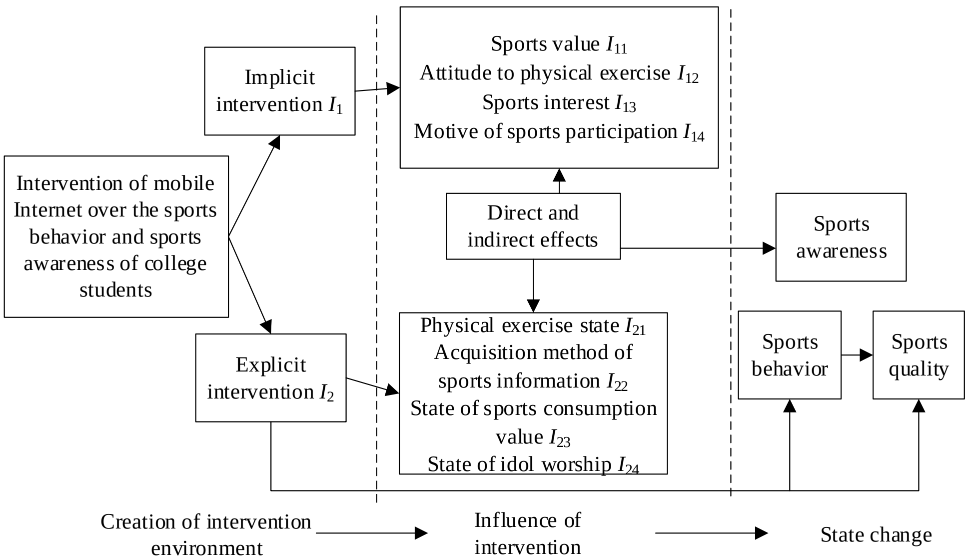

Figure 1. Action mechanism of intervention events

The topology of the intervention event network has three primary features: node features, node centrality, and network centrality. The node feature reflects the global features of the network, while the node and network centralities reveal the key intervention events and node difference, respectively.

2.2 Static structural analysis

For node feature analysis, this paper chooses degree distribution as the criterion to judge whether the proposed intervention event network is a scale-free network. If yes, then the degree of the network obeys the power law distribution. The node probability is proportional to a power of the degree l:

$$FB(l) \propto l^{-\beta}, -2 \leq \beta \leq 3 \quad (1)$$

Since the intervention event network is small, and the statistical feature of $FB(l)$ is not very significant, i.e., nodes with a large l may exist at the tail of the network degree distribution function. To reduce the statistical deviation, the degree distribution $FB(l)$ is described by the cumulative degree distribution function FB_l. Then, the FB_l of the scale-free intervention event network obeys the power law distribution with the power exponent of β-1:

$$FB_l \propto \sum_{a=l}^{\infty} a^{-\beta} \propto l^{-(\beta-1)} \quad (2)$$

For node centrality analysis, this paper describes the centrality of the intervention event network with network degree, closeness, and betweenness. The degree $F_T(i)$ of a network of the size m can be defined as:

$$F_T = \frac{\sum_{i=1}^{m}[F_T^*(i) - F_T(i)]}{max\sum_{i=1}^{m}[F_T^*(i) - F_T(i)]} \quad (3)$$

where, $F^*_T(i)=maxF_T(i)$. Since the node degree falls in $[1,m-1]$, $max\Sigma^m_{i=1}[F^*_T(i)-F_T(i)]=[(m-1)-1]=m^2-3m+2$. Thus, formula (16) can be simplified as:

$$F_T = \frac{\sum_{i=1}^{m}[F_T^*(i) - F_T(i)]}{m^2-3m+2} \quad (4)$$

The closeness $F_f(i)$ of a network of the size m can be defined as:

$$F_f = \frac{\sum_{i=1}^{m}\left[F_f^*(i) - F_f(i)\right]}{max\sum_{i=1}^{m}\left[F_f^*(i) - F_f(i)\right]} \quad (5)$$

where, $F^*_f(i)=maxF_f(i)$. If the distance from node i to any other node is 1, and if the distance between any two nodes except node i is 2, then the maximum closeness of node i is 1, and the minimum closeness of the nodes except node i is $1/2m$-3. Thus, formula (18) can be simplified as:

$$F_f = \frac{2m-3}{2(m^2-3m+2)}\sum_{i=1}^{m}\left[F_f^*(i) - F_f(i)\right] \quad (6)$$

The betweenness $F_Y(i)$ of a network of the size m can be defined as:

$$F_Y = \frac{\sum_{i=1}^{m}[F_Y^*(i) - F_Y(i)]}{max\sum_{i=1}^{m}[F_Y^*(i) - F_Y(i)]} \quad (7)$$

where, $F^*_Y(i)=maxF_Y(i)$. Since the node betweenness belongs to $[0,(m-1)(m-2)]$, $max\Sigma^m_{i=1}[F^*_Y(i)-F_Y(i)]=[(m-1)(m-2)-(m-1)]$. Thus, formula (20) can be simplified as:

$$F_Y = \frac{\sum_{i=1}^{m}[F_Y^*(i) - F_Y(i)]}{m^3-4m^2+5m-2} \quad (8)$$

To measure the difference between network nodes, this paper computes network degree, closeness, and betweenness on Pajek 5.08.

3. Action Mechanism Analysis

Based on the proposed intervention event network, this paper relies on the system event analysis, a mature tool in complex system research, to deeply analyze the interactive relationship between different intervention events in the network, and quantify the composite degree of influence between them.

In traditional system event analysis, the relevant variables are processed by triangular fuzzy numbers as follows:

If there exists a membership function $v_\psi(a)$: $R\rightarrow[0,1], a\in R$, then:

$$v_\psi(a) = \begin{cases} 0, if\ else \\ \frac{a-k}{n-k}, k < a \leq n \\ \frac{s-a}{s-n}, n < a \leq s \end{cases} \quad (9)$$

Then, a triangular fuzzy number $\psi=(k,n,s)$, $k\leq n\leq s$ can be defined on the real domain.

In this paper, the evaluated states of college students' sports behavior and sports awareness in the context of mobile Internet are converted into a triangular fuzzy number (k^l_{ij}, n^l_{ij}, s^l_{ij}), which reflects the degree of influence of event i over event j during the state judgement of sports behavior and sports awareness of subject l. Then, (k^l_{ij}, n^l_{ij}, s^l_{ij}) is converted into a precise value to defuzzify the judgement results. The specific steps are as follows:

Step 1. To reduce the subjective difference of state judgements, normalize the relevant data by:

$$ak_{ij}^l = \frac{k_{ij}^l - \min_{l\leq l\leq L} k_{ij}^l}{\Delta_{min}^{max}} \quad (10)$$

$$an_{ij}^l = \frac{n_{ij}^l - \min_{k\leq l\leq L} k_{ij}^l}{\Delta_{min}^{max}} \quad (11)$$

$$as_{ij}^l = \frac{s_{ij}^l - \min_{k\leq l\leq L} k_{ij}^l}{\Delta_{min}^{max}} \quad (12)$$

where, $\Delta^{max}_{min}=max_{1\leq l\leq L}s^l_{ij}-min_{1\leq l\leq L}k^l_{ij}$。

Step 2. Let akr^l_{ij}, asr^l_{ij}, and a^l_{ij} be the left, right, and overall standard values, respectively. Then, convert the normalized fuzzy number into akr^l_{ij} and asr^l_{ij} by:

$$akr_{ij}^l = \frac{an_{ij}^l}{1+an_{ij}^l+ak_{ij}^l} \quad (13)$$

$$asr_{ij}^l = \frac{as_{ij}^l}{1+as_{ij}^l+an_{ij}^l} \quad (14)$$

Then, transform akr^l_{ij} and asr^l_{ij} into a^l_{ij} by:

$$a_{ij}^l = \frac{akr_{ij}^l\left(1-akr_{ij}^l\right)+asr_{ij}^l asr_{ij}^l}{1-akr_{ij}^l+asr_{ij}^l} \quad (15)$$

Step 3. Quantify the degree of influence of event i over event j during the state judgement of sports behavior and sports awareness of subject l by:

$$x_{ij}^l = \min_{k\leq l\leq L} k_{ij}^l + a_{ij}^l \Delta_{min}^{max} \quad (16)$$

Quantify the entire ternary fuzzy number, i.e., the degree of influence of event i over event j during the state judgement of all subjects, by:

$$x_{ij} = \frac{1}{l}\sum_{l=1}^{l} x_{ij}^l \quad (17)$$

This paper calculates the relationships between the events, using the functions embedded in Excel and the self-designed VBA programs. Let X be the direct influence matrix; T be the normalized influence matrix. Then, X can be converted into T by:

$$T = \frac{1}{\max_{k\leq i\leq 15}\sum_{j=1}^{15} x_{ij}} X \quad (18)$$

Let D be the total influence matrix. Then, T can be converted into D by:

$$D = T(\theta - T)^{-1} \quad (19)$$

Finally, the sum of each row s_i and the sum of each column f_j in D can be respectively calculated by:

$$s_i = \sum_{j=1}^{15} p_{ij} \quad (20)$$

$$f_j = \sum_{i=1}^{15} d_{ij} \quad (21)$$

where, s_i is the total influence of event i over other events, i.e., the degree of influence T of event i; f_i is the total influence of other events over event i, i.e., the degree of being influenced S of event i. If $i=j$, then s_i+f_j is the importance of the influence of event i over the state of college students' sports behavior and sports awareness, and can be regarded as the centrality $T+S$. Meanwhile, s_i-f_j can be regarded as the cause degree $T-S$. If $s_i-f_j>0$, then event i is the cause of the state change of college students' sports behavior and sports awareness; if $s_i-f_j<0$, then event i is the result of the state change of college students' sports behavior and sports awareness.

4. Action Mechanism Modeling

In the preceding section, the key intervention events are recognized through the in-depth analysis on their interactive relationships in the network. This section aims to adopt the integrated fuzzy-interpretative structural model to reveal the internal logic and action mechanism of the event-based hierarchy model.

This paper superimposes matrices D and H into the composite influence matrix $M=H+D$ of the intervention events. The threshold ε can be determined based on matrix M, so as to continuously optimize the structure of the event-based hierarchy model. Further computation would solve the reachability matrix N of the events affecting the state of college students' sports behavior and sports awareness:

$$x_{ij} = \begin{cases} 1, x_{ij} \geq \varepsilon \\ 0, x_{ij} < \varepsilon \end{cases}, \quad (i = 1,2,\ldots,36; j = 1,2,\ldots,36) \quad (22)$$

Based on the reachability matrix N, it is possible to derive the reachable set $L(N_i)$, antecedent set $A(N_i)$, and collective set $E(N_i)$ for the events affecting the state of college students' sports behavior and sports awareness:

$$L(N_i) = \{N_i | x_{ij} = 1\}$$
$$A(N_i) = \{N_j | x_{ij} = 1\}$$
$$E(N_i) = L(N_i) \cap A(N_i) \quad (23)$$

If two intervention events belong to the same $L(N_i)$ and $E(N_i)$, then they will be treated as layer i events λ_i of the event-based hierarchy model:

$$\lambda_i = \{N_j | N_j \in N - \lambda_0 - \lambda_1 - \ldots - \lambda_{i-1}, L(N_i) = E(N_i)\} \quad (24)$$

After identifying λ_i, the relevant intervention events are eliminated. The same operation is repeated in search of the events on the next layer, until the action mechanism of all events is fully disclosed.

5. Experiments and Results Analysis

The intervention indices were obtained by summing up the frequency and loss degree of each intervention event, multiplying the values of the two parameters, and taking the average of the products. The values of these indices are recorded in Table 1.

Table 1

Indices of intervention events

Intervention event	Intervention index	Intervention event	Intervention index	Intervention event	Intervention index	Intervention event	Intervention index
I_{111}	5.16	I_{122}	3.47	I_{142}	8.11	I_{216}	0.24
I_{112}	4.25	I_{123}	3.48	I_{143}	3.62	I_{221}	0.36
I_{113}	7.42	I_{124}	7.42	I_{144}	4.07	I_{222}	3.82
I_{114}	5.68	I_{131}	6.18	I_{145}	3.28	I_{223}	3.68
I_{115}	3.28	I_{132}	6.59	I_{211}	3.61	I_{231}	1.74
I_{116}	3.36	I_{133}	7.85	I_{212}	3.72	I_{232}	4.26
I_{117}	4.18	I_{134}	5.12	I_{213}	3.09	I_{241}	5.58
I_{118}	3.64	I_{135}	8.05	I_{214}	4.16	I_{242}	5.92
I_{121}	0.82	I_{141}	6.48	I_{215}	3.57		

Based on frequency and loss degree, this paper establishes a dual criteria matrix for the intervention events (Table 2). It can be seen that five intervention events have a relatively strong influence over the sports behavior and sports awareness of college students, namely, I_{212}, I_{141}, I_{143}, I_{144}, and I_{221}. Thus, the state of college students' sports behavior and sports awareness would change, if any of the five events takes place (i.e., school performance, entertainment and relaxation, bodybuilding, frequency of physical exercises, and new media).

This paper computes the node degree, closeness, and betweenness of the network. Based on Pajek 5.08, the centrality values of some nodes were obtained (Table 3). As shown in Table 3, I_{212}, I_{141}, I_{143}, I_{144}, and I_{221} were the top five nodes by degree centrality. These events have a relatively high influence in the network. I_{122}, I_{123}, I_{124}, I_{131}, and I_{242} were the top five nodes by closeness centrality. These events are closely correlated with each other. I_{132}, I_{133}, I_{134}, I_{135}, and I_{214} were the top five nodes by betweenness centrality. These events are the hub of the network. Figures 2-4 provide the cause-effect diagrams of events on Layers 3, 2, and 1, respectively. The influence, centrality, and proactiveness of events on each layer can be clearly seen in these diagrams.

Table 4 sorts out the *T*, *T+S*, and *T-S* values of Layer 2 intervention events for the influence of mobile Internet over the sports behavior and sports awareness of college students. To demonstrate the effectiveness of our action mechanism model for network intervention events, the cause-effect diagrams of Layer 1 intervention events were plotted at different thresholds ε (Figure 5), and the test results of the model were obtained (Table 5).

Table 2

Dual criteria matrix for the intervention event

	Strongly large	Slightly large	General	Slightly small	Strongly small
Strongly rare	I_{142}				I_{222}, I_{223}
Slightly rare				I_{117}, I_{118}, I_{121}	I_{231}, I_{232}
General		I_{211}, I_{213}			
Slightly frequent	I_{122}, I_{123}, I_{124}, I_{131}, I_{242}	I_{111}, I_{112}, I_{215}, I_{216}		I_{114}, I_{115}, I_{116}, I_{241}	I_{132}, I_{133}, I_{134}, I_{135}, I_{113}, I_{214}
Strongly frequent	I_{145}	I_{212}, I_{141}, I_{143}, I_{144}, I_{221}			

Table 3

Centralities of some nodes

Ranking	1	2	3	4	5
Intervention node	I_{212}	I_{141}	I_{143}	I_{144}	I_{221}
Degree centrality	0.325	0.336	0.351	0.208	0.211
Intervention node	I_{122}	I_{123}	I_{124}	I_{131}	I_{242}
Closeness centrality	0.518	0.462	0.433	0.428	0.415
Intervention node	I_{132}	I_{133}	I_{134}	I_{135}	I_{214}
Betweenness centrality	0.328	0.224	0.175	0.139	0.118

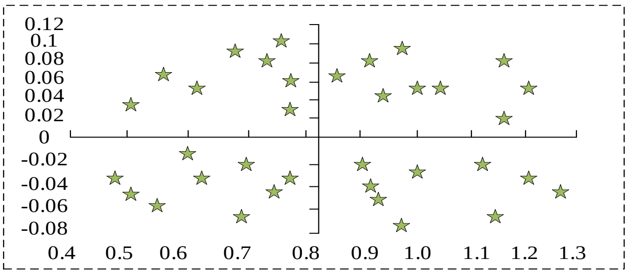

Figure 2. Cause-effect diagram of Layer 3 events

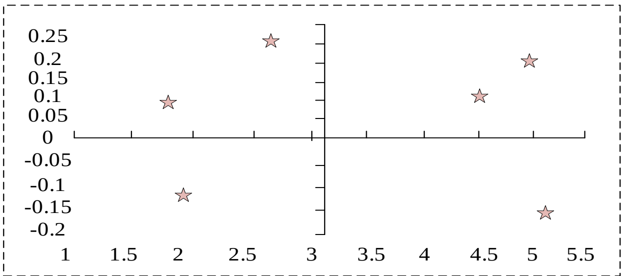

Figure 3. Cause-effect diagram of Layer 2 events

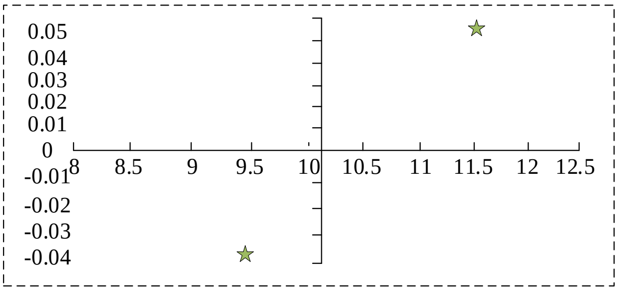

Figure 4. Cause-effect diagram of Layer 1 events

Table 4

T, T+S, and T-S values of Layer 2 events

Implicit intervention	I_{11}	I_{12}	I_{13}	I_{14}
D	1.1257	0.7251	0.8063	1.3268
D ranking	6	8	7	3
R	1.0852	0.7481	0.9253	1.3526
R ranking	4	8	7	3
D+R	2.0158	1.6235	1.5827	2.8625
D+R ranking/weight	6(0.0658)	7(0.0428)	8(0.0582)	3(0.1328)
D-R	-0.0849	-0.0358	0.0295	0.0968
D-R ranking	7	6	4	1
Explicit intervention	I_{21}	I_{22}	I_{23}	I_{24}
D	1.7135	1.1485	1.2625	1.3869
D ranking	1	5	4	2
R	0.9352	1.0748	1.3625	1.9485
R ranking	6	5	2	1
D+R	3.6281	2.7485	3.0625	2.1893
D+R ranking/weight	1(0.1628)	4(0.0629)	2(0.0684)	5(0.0758)
D-R	0.0958	-0.0274	-0.1069	0.0856
D-R ranking	2	5	8	3

The test indices include C.R. value and P value. The former is the ratio of the estimated value of a parameter to its standard deviation. As shown in Table 5, the C.R. value and P value of I_{14} were 1.529 (<2) and 0.059 (>0.05). Thus, the intervention event has a relatively insignificant correlation with other intervention events. The paths between the other intervention events all passed the significance test at the level of 0.05.

Table 5

Test results on the action mechanism model for network intervention events

Implicit intervention	I_{11}	I_{12}	I_{13}	I_{14}
Standard regression coefficient	0.362	0.295	0.402	0.825
Standard deviation	0.085	0.135	0.114	0.085
C.R. value	4.162	2.158	3.628	1.529
P value	0.001	0.000	0.016	0.052
Support (Yes/No)	Yes	No	Yes	Yes

Explicit intervention	I_{21}	I_{22}	I_{23}	I_{24}
Standard regression coefficient	0.847	0.925	0.963	0.858
Standard deviation	0.083	0.102	0.072	0.639
C.R. value	2.842	3.263	4.184	3.268
P value	0.028	0.001	0.008	0.006
Support (Yes/No)	Yes	No	Yes	Yes

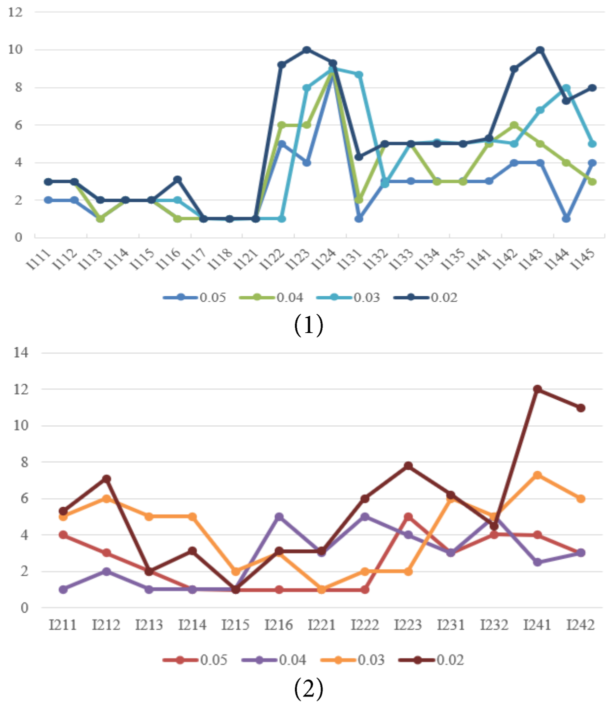

Figure 5. *Cause-effect diagrams of Layer 1 intervention events at different thresholds ε*

6. Conclusions

Inspired by the existing literature, this paper thoroughly examines the intervention of mobile Internet on the sports behavior and sports awareness of college students. Firstly, the authors set up an intervention event network for the influence of mobile Internet over the sports behavior and sports awareness of college students, and carries out a statical structural analysis. Then, system event analysis, a mature tool in complex system research, was introduced to deeply analyze the interactive relationship between different intervention events in the network, and to quantify the composite degree of influence between them. After that, the integrated fuzzy-interpretative structural model was adopted to clarify the internal logic and action mechanism of event-based hierarchy model. Based on experimental results and the indices of intervention events, the authors established a dual criteria matrix for these events, computed the node degree, closeness, and betweenness in the network, and gave the centrality values of some nodes. In addition, the cause-effect diagrams were prepared for events on Layers 1-3, providing a visual display of the influence, centrality, and proactiveness of events on each layer. Finally, the *T*, *T+S*, and *T-S* values of Layer 2 intervention events were solved, and the test results on the action mechanism model were obtained. The results show that the paths between most intervention events passed the significance test at the level of 0.05.

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