Is Data Panel Beneficial for Mental Health Assessment?

Yuan Guofan[1], Xiong Li[1], Wang Huiqiu[1]

1 Guangzhou Huashang Vocational College

Funding: No specific funding was received for this work.

Potential competing interests: No potential competing interests to declare.

Abstract

Background: Symptom Checklist 90 (SCL-90) and University Personality Inventory (UPI) are commonly used mental health scales. SCL-90 reflects subject's mental state, while UPI reflects subject's psychological adjustment ability. The combination of the two scales helps to construct a comprehensive profile of mental health. However, few studies discuss how to combine the two scales and the test results are mainly present in the form of static cross-sectional images, lacking a visual platform and user interaction interface.

Subjects and Methods: The data from 926 college freshmen by means of SCL-90 and UPI was collected. A dynamic data panel is advocated and presents static mental health data in an interactive way.

Results: Cluster model was set to combine SCL-90 with UPI, 9 clusters indicated the maximum Calinski-harabasz score (CH = 3010). The data panel helps detect the conflicts in terms of dormitories.

Conclusions: The classification of mental health seriousness from traditional measurement should not beyond 9 kinds. A new method to combine mental state with psychological adjustment ability is through data panel with panel data models applied. Latent growth curve model (LGCM) is available in time-based data panel and convolution neuron network (CNN) is useful in group-based data panel which is beneficial for mental health assessment.

Keywords: PyEcharts library - mental health - data panel - interactive interface.

Introduction

Symptom Check List (SCL-90) and University Personality Inventory (UPI), which are commonly viewed as the effective tools screening mental health problems, are able to provide reliable testing results for college students' mental health indication due to their good fit in the framework of the classical test theory in which the systematic variance of test data is maximized and the unsystematic variance of test data is expected to be minimized (Kieffer 1998). The two scales have been consistently reported good reliability and validity in various studies (Zhang & Zhang 2013, Wang et al 2017). The measured results by SCL-90 and UPI have clinically practical significance, therefore being widely adopted for mental health measurement (Shi et al. 2013, Wang 1995).

The measure of SCL-90 yoking to UPI exhibits huge advantage compared to the single scale test by either SCL-90 or UPI. Some studies have shown that the two scales, SCL-90 and UPI, have certain internal correlations (Wang 1995), and their combined test may be more accurate than the single scale test, which can significantly improve the positive rate of screening, thereby objectively and comprehensively reflecting the mental health levels of college students (Lin 2007). As Shen et al. (2010) have pointed out that there was complementarity between UPI and SCL-90, the two methods should be applied jointly in testing and intervention phase for the improvement of mental health levels for college students.

The reasons for the integration of the two scales mainly come from two aspects. On the one hand, the combination of the two scales provides more information about college students' mental health rather than the single scale test, not only can the severe levels of mental health be judged by the classification of UPI that relies on normative data, but also can the specific symptoms be analyzed for the subjects by SCL-90 measurement; On the other hand, combined test is more comprehensive than the single scale test which only adopts one scale for testing. Combined test constellates more constituent facets of mental health such as positive mental state and strong psychological adjustment ability, whereas single scale test purely reflects one aspect of them.

Combined test of UPI and SCL-90 makes the test of mental state integrated into that of mental adjustment ability which is equivalent to integrating test of unstable and temporary emotional status into test of stable and long-term personality trait and ability, therefore, combined test enables the assessment of mental health more adequate and full-fledged. Shan (1998) has proposed that the construct of mental health should include two closely related but differentiated parts, namely, mental state and psychological adjustment ability. SCL-90 reflects the frequency of mental health problems in a very short period about one week. In this sense, SCL-90 merely tests the recent mental states of college students, while UPI reflects the frequency of mental health problems over a longer period about one year, therefore, psychological adjustment ability that refers to the ability to regulate one's mental health levels and the resilience related to personality traits which helps students recover from the mental health problems or even suicide (Patricia et al. 2021) will be embodied in UPI measurement for it asks subject about the incidence of various mental health problems in about one year.

The two scales should be integrated and when combined, psychological test can better reflect the overall picture of mental health. Therefore, many universities prioritize the use of the two scales for combined test when screening out the mental health issues for college freshmen. However, the method to combine the two scales is flexible and researchers scarcely make an agreement on it, i.e., some researchers give priority to UPI and take the results of SCL-90 as a reference, while others take the opposite.

Noteworthy, when combining the two scales, it's easy to unrealistically exclude subjects with mental health problems or include subjects without mental health problems in the healthcare list when the method to combine the two scales is not standardized. Neither of the mentioned methods that gives priority to SCL-90 or UPI is conclusive leading to the high rate of false negative screening. Therefore, in order to make the combined test more inclusive and conclusive, a new view in this study is given for the combination of the two scales, that is, cluster model in machine learning can be applied to melt the test result of SCL-90 into that of UPI, and user can gain a conclusive result to screen out those students with mental health problems by the unsupervised cluster model. Thus, one of the research goals is to use cluster model to show how to combine SCL-90 with UPI conclusively.

The university departments for psychological education and consultation can collect students' mental health data through SCL-90 and UPI, and figure out individuals with psychological problems based on cluster models such as K-means or DBSCAN, ultimately identifying the population with mental health problems or mental symptoms, and furthering psychological tracking and intervention for this part of population. In this process, the psychological scale plays an important role on problem screening and auxiliary diagnosis. However, considering the type I and type II errors that can occur in the psychological measurement process, the diagnostic results from psychological scales may not necessarily be fully consistent with the actual situation. Therefore, a comprehensive judgment needs to be made in combination with psychological interviews and surveys of individual's growth background and history of mental illness.

Psychological test is usually regarded as a part of the intake interview in psychological counseling, and its contribution to the clinical diagnosis is limited. It is generally filed after the diagnosis is completed, so the quantitative data obtained through psychological scale test is easily ignored and has a low utilization rate. For instances, for individual with psychological symptoms, the results obtained through psychological test may manifest negative symptoms if the individual completes the scale items under the influence of physical fatigue, feeling of over tediousness, social approval effect, or other unsystematic measurement errors, that is, there are false negative symptoms and type II error existing in the test. In order to avoid misjudgment of the actual situation and reduce the incidence of type I and type II error, psychological counselor often needs to use in-person interviews as the final basis for diagnosis, and psychological test is just one way to assist diagnosis. Psychological test usually works for the referent assessment, and does not determine the final diagnostic results. Therefore, the data obtained through psychological scales will subsequently be archived at the end of the preliminary consultation, and cannot be adequately displayed and analyzed, nor can it be utilized and updated in a real-time and dynamic manner.

In practical work, most psychological counselors only use psychological test data to screen out groups with suspected mental health problems, and in the subsequent psycho-counseling process, they no longer use the psychological test results as a referent pool. Instead, they pay more attention to the diagnosis obtained from psychological interviews than the quantitative test data, they often call the clinical interview as the gold standard to address the importance of clinical interview (Giovanni 2023). This approach has its rationality, but it is easy to overlook the full use of psychological test data, ignoring the possibility of detecting any subtle details about the individual experience through horizontal and vertical comparison of psychological test data. So the other goal in this research is to use data panel to compare the mental health data horizontally and vertically, find out the subtleties and reveal the reason why students go through the change of mental health.

Methods

A sample of 926 college freshmen aged between 18-21 was recruited who consented to approach the data under the condition of anonymity for scientific goal which obeys the declaration of Helsinki version 2008. The ethics committee of college agreed the research protocol.

Melting SCL-90 into UPI

As one of the goals in this research is to combine the test of SCL-90 into that of UPI to show the whole picture of mental health which should include individual mental state and psychological adjustment ability, hierarchical cluster model was adopted to analyze the structure of psychological symptoms (i.e., comorbidity among systems) and K-means cluster model was applied to fulfill the combination of SCL-90 and UPI. Every symptom score in SCL-90 and the total score of the uni-dimensional UPI are taken into consideration in the cluster model using Euclidean distance to acquire the optimal class (Yang et al. 2006).

However, K-means cluster model is the unsupervised classification model where K representing the number of classes is not given in the data, therefore, a metric is needed to indicate the goodness of the models for different number of clusters. This study uses Calinski-habarasz scores as indices for the goodness of models with different K values.

The construction of data panel with horizontal data

As the other goal of the research is to compare the mental health data horizontally and vertically, Pyecharts library was employed to construct the data panel (Other tools are available). The full excavation on the potential value of test data is contingent on the horizontal and vertical comparisons of mental health data. The horizontal comparison of psychological test data can be traced back to the collection of horizontal data which shows the inter-group levels at a given time, whereas the vertical comparison of data is a comparison of psychological health levels based on personal longitudinal experience accumulated by daily or weekly collected data lasting a certain length of time.

The horizontal comparison helps to timely detect individual or group differences. By comparison of mental health levels of individuals or groups from horizontal data, group variance and individual difference can be detected in time so as to properly intervene extreme behaviors such as hurting oneself or behaving beyond the permission of laws, and that relieve feeling of stress caused by life events. In addition, if combining with convolution neuron network (CNN) in the field of artificial intelligence (AI) and utilizing the video surveillance system on campus, the horizontal comparison can express individual’s daily emotional status like data intelligent analysis system (Yu 2023). Moreover, horizontal data sourcing from video can also conquer the time restriction like vertical data and constantly flow into the AI model to provide more accurate prediction for the variation of mental health based on the training of data stream from the campus surveillance system if technically available and legitimately possible.

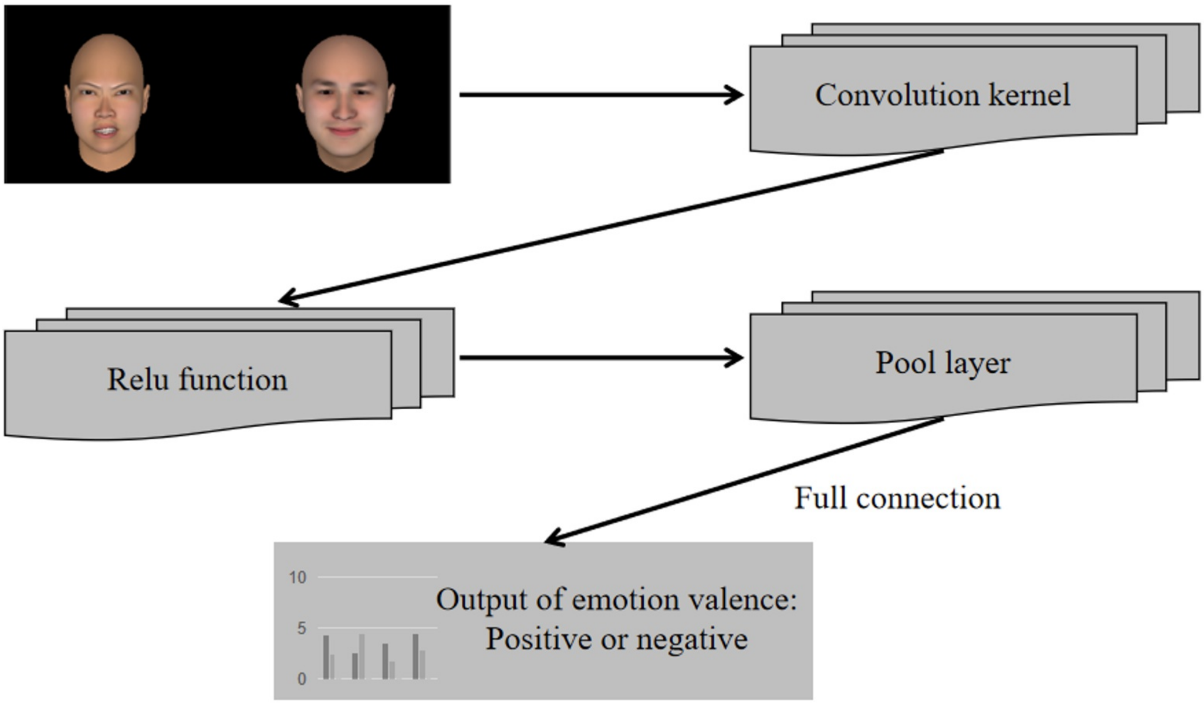

Figure 1. Application of CNN for recording students' emotion status.

As seen in Figure 1, CNN contains three components, that is, convolution kernel, Relu or softmax function, pool layer. A deep convolution neuron network can be set up by repeating convolution kernel and pool layer in the configuration of CNN. In order to construct CNN model to better predict subject's emotional valence and record individual's daily psychological state over time, Pytorch or Tensorflow in Python can be borrowed up to conveniently set up the CNN model (Florencio et al. 2019). By means of virtual face photos as input data to train the CNN model to accurately predict the valence of facial emotion, a well trained CNN model will be eventually obtained so as to deal with the unstructured pixel data. After that, real facial information gained from campus surveillance system can be used as input data and the well trained CNN model is deployed to generate the emotion valences of college students from campus surveillance system. The emotional status can be recorded in every student's personal archive of mental health, at the same time, prediction accuracy, recall rate and F1 score of the trained CNN model can be calculated by confusion matrix via cross-validation to check the performance of the model.

The feasibility of using CNN to detect the change of psychological states among college students is due to the premium property of CNN in the field of facial recognition and feature extraction. As Mahadevkar et al. (2022) have pointed out that one of the tasks the convolution neural network successfully completes for successful object detection is feature extraction. Mahadevkar et al. (2022) have further argued that with a big collection of face photos, a deep convolution neural network can recognize faces through supervised learning. Thus, combining with virtual face photos generated by the software such as Facegen as seen in Figure 1, a convolution neuron network can be built and trained to effectively recognize the face and the valence of facial emotion, the pixel data stream is recorded and converted as college students' daily emotional states to overcome the insufficiency of horizontal data comparison for its inability to track individual's psychological state during different period.

The construction of data panel with vertical data

The vertical comparison of psychological test data is a comparison of psychological health levels based on personal longitudinal experience, which is a dynamic display of psychological health levels collected at different point of time. Through the display of longitudinal data, psychological counselors can identify the negative impact of objective environment on individual mental health or other causes of mental health issues in the framework of Kelley's attribution theory.

Through vertical comparisons, individual's psychological adjustment ability is highlighted on the panel. For instances, if individual's mental health level is always higher than others, it is convincing that the individual's psychological adjustment ability is stronger. If individual's mental health trajectory hits the valley bottom and always automatically bounce back to a relatively high level, the strong psychological adjustment ability is also signaled from the vertical data.

The time-based data panel sourcing from vertical data can show the curve of mental health fluctuation for individual. Besides, the time-based mental health data panel can also compare different growth curves of mental health within various groups by combining with the latent growth curve model (LGCM) which is increasingly used in social science to analyze longitudinal data (Geiser 2012). LGCM is useful to describe the group difference over time based on the time series data (As seen in Figure 2, the decrease of the red line demonstrates the upward trend of group's average mental health levels based on the measurement of SCL-90 which may result from the fear receding from Covid-19 pandemic due to the proper measures taken by the government and the relevant faculties). The time-based panel will provide the representative information of groups when combining with LGCM with auto-regressive effect retrieved.

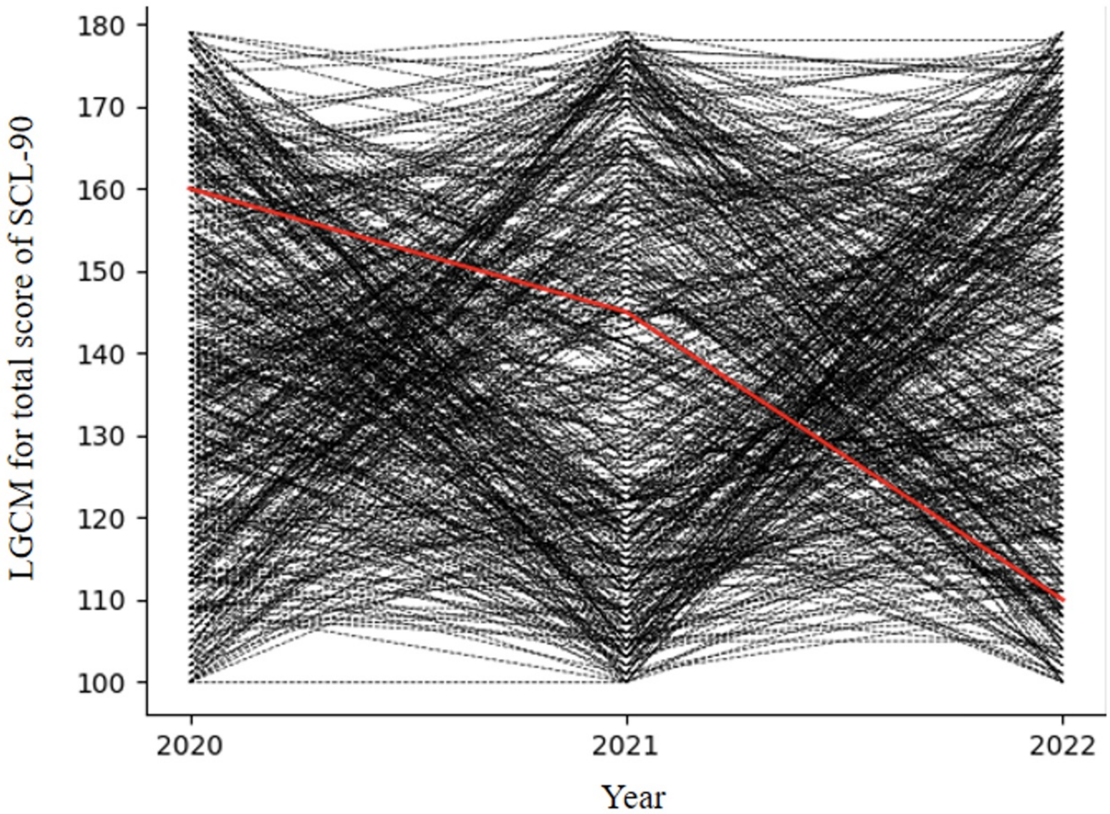

Figure 2. Latent growth curve model (LGCM) for vertical data collected by SCL-90.

In LGCM, the representative trajectory of mental health in the sample can be isolated from the sample's inner characteristic, i.e., the intercept in LGCM represents the sample's inner characteristic and slope embodies the variant trend of characteristics (Tan et al. 2021). In this case, intercept of LGCM reflects the levels of mental health of the sample in the initial wave, and the slope in LGCM indicates the representative growth curve of mental health in the subsequent waves. By dividing sample into various subgroups, the mental health trajectory of distinct subgroups can be compared like group comparison in horizontal data analysis. In this sense, LGCM compensates for the insufficiency of vertical data in which it's incapable of comparing the growth curves between different subgroups.

Results

Means for combination of SCL-90 and UPI

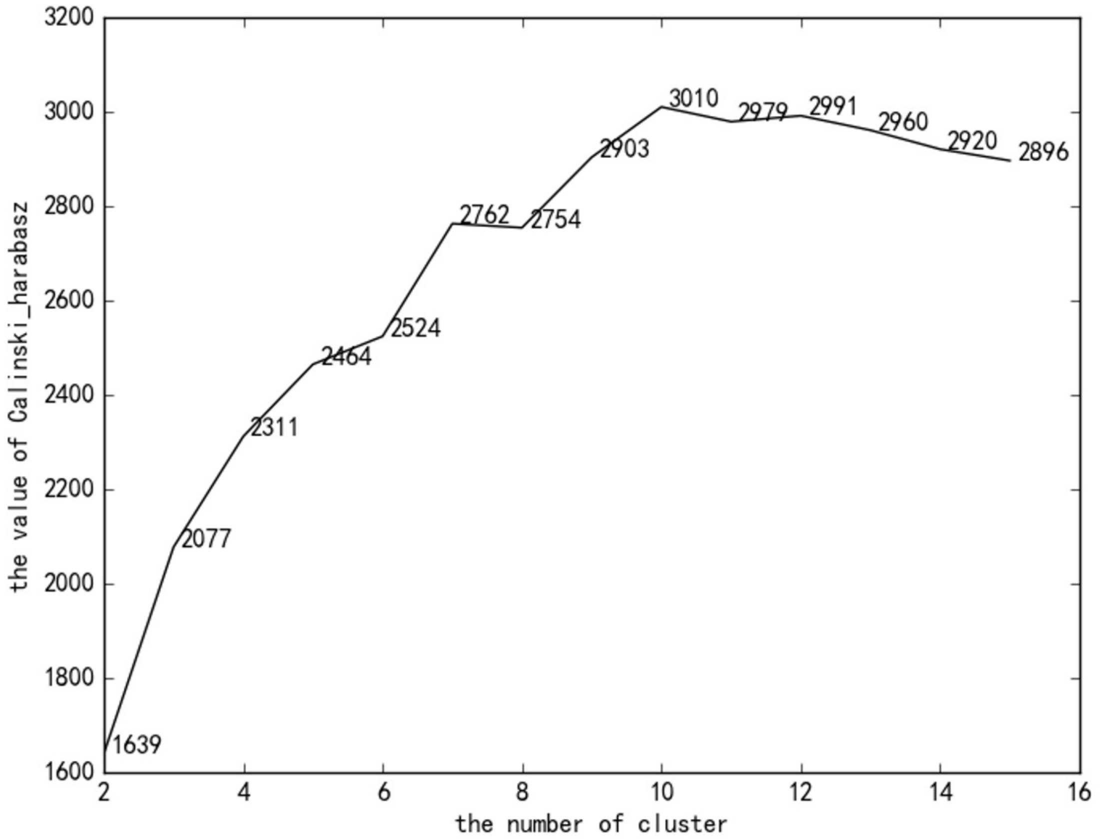

Figure 3. The model fit for different number of clusters

As seen in Figure 3, Calinski-habarasz score is used to evaluate the goodness of the model fit for different K values. Calinski-habarasz score represents the ratio of trace of between-cluster matrix and that of inner-cluster matrix. The bigger the Calinski-habarasz score, the better the cluster model. When the cluster number is set to be 9, the score is the best which is 3010.

The analytical result in Figure 3 show that when the cluster is less than 9, more clusters usually indicate the better model fit. However, the number of clusters should also cater to the theoretical explanation, so we set the K clusters to be 4 for convenience. The individuals with severe psychological health issues can be figured out from the cluster model in which k value is assumed to be 4 ranging from the worst mental health class to the healthiest class with both high score of SCL-90 and UPI as indicators of mental health seriousness (Wang & Wang 2020).

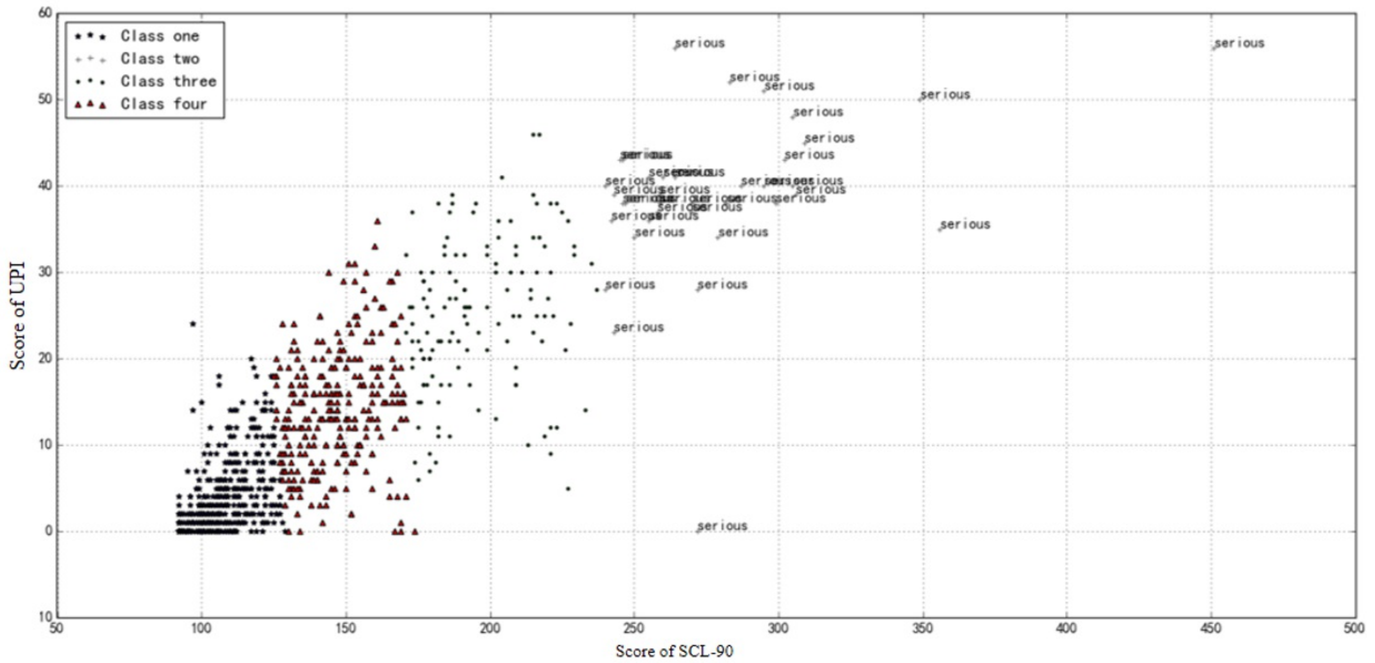

Figure 4. K-means cluster model combined the testing result of SCL-90 with UPI.

As seen in Figure 4, the K-means classification model informs psychological counselors and educators about the listed students to whom they should pay attention. When both of the score of SCL-90 and UPI are higher which means the scatter points locate on the upper right corner, the worse the mental health for the corresponding individual.

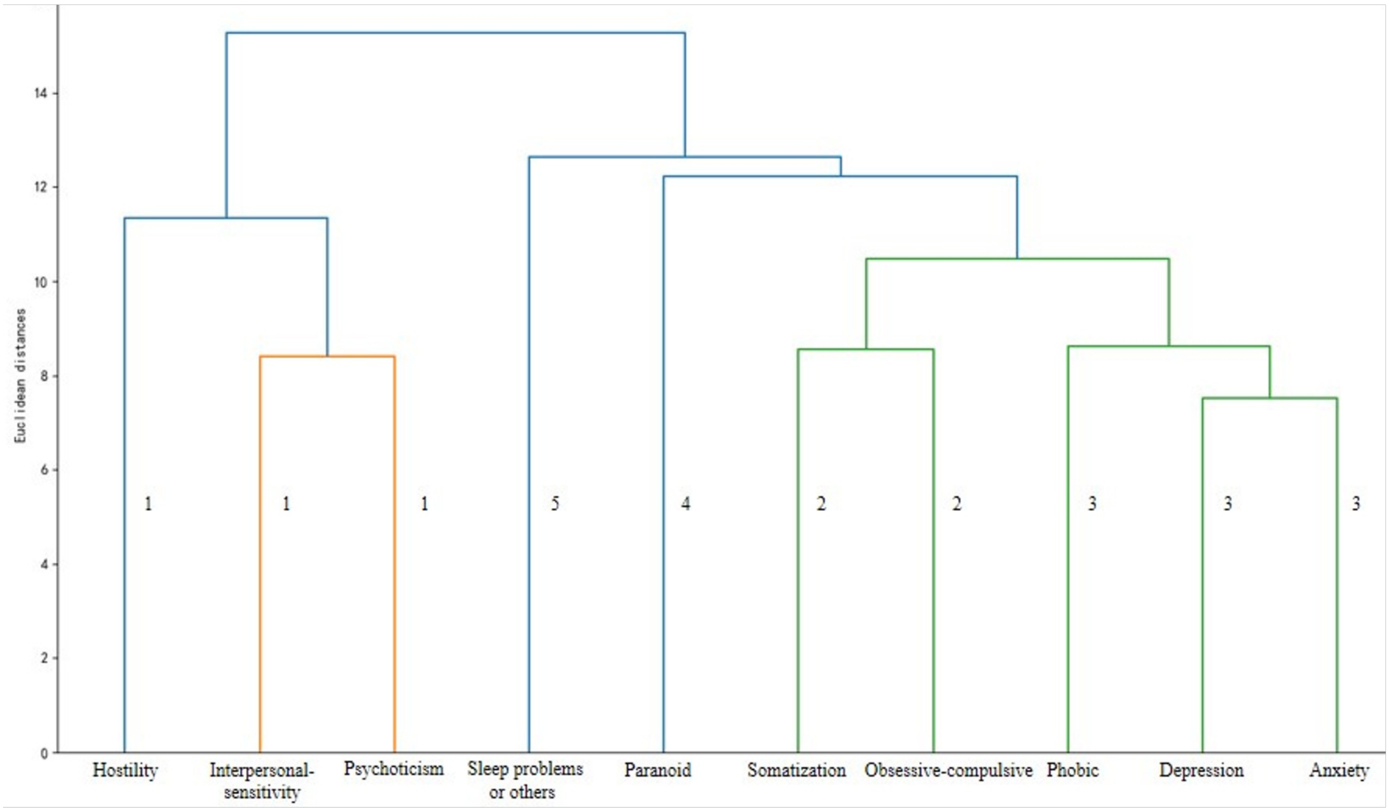

Figure 5. Hierarchical cluster model to disclose comorbidity among symptoms

In order to exhibit the structure among various symptoms, hierarchical cluster model is used to analyze the comorbidity for each pair of symptoms. As shown in Figure 5, psychoticism, interpersonal-insensitivity and hostility are likely to co-occur as comorbidity for this sample with attribution to class 1; Whereas somatization and obsessive-compulsive are comorbidity by attributing to class 2; Phobic, depression and anxiety are comorbidity attributing to class 3. Paranoid, sleep problems/others seem to happen independently.

The construction of data panel

To elucidate the usefulness of horizontal data comparison, the data comparison by groups can be refined to the dormitory as seen in Figure 5. The mental health levels of college students in the same dormitory often share the common ground because of the mutual influence between each other, which is displayed through a dynamic data panel based on groups. Psychological counselors have noticed that everyone in a dormitory has a low level of mental health compared to other dormitories. Through further interviews and conversations, it has been found that the marked dormitory has serious interpersonal conflicts and misunderstandings due to various daily schedules among the dormitory members, further intervention can then be practiced in solving the dormitory conflicts. The dynamic data panel based on dormitory comparison has contributed to the timely detection of dormitory conflicts and the timely prevention of problematic behaviors, which is of significance in college management due to the abruptness of crisis events.

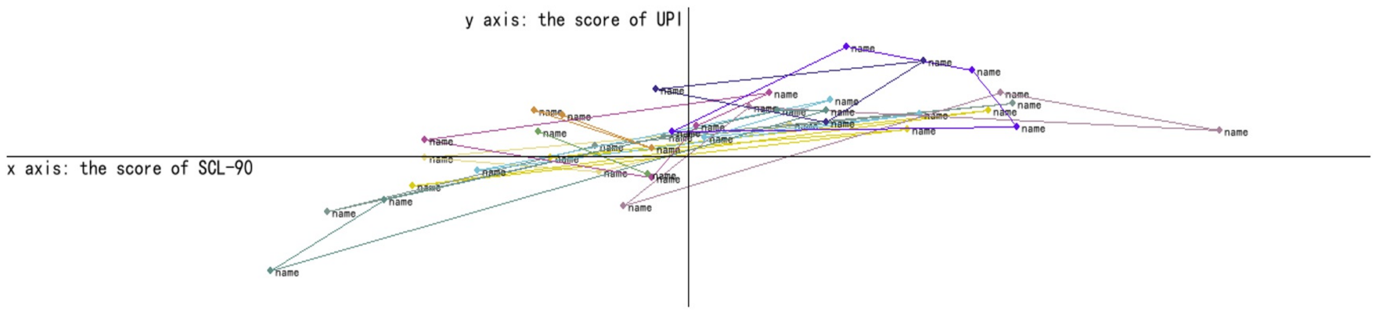

Figure 6. The horizontal comparison of mental health data by dormitory in data panel

As seen in Figure 5, the lines between the two nodes mean the two persons live in the same dormitory. If the points on the upper right corner link between each other, then it means the individuals represented by the nodes live together with serious mental health problems, which further indicates that some conflicts may exist in that dormitory.

By constructing a group-based dynamic data panel, the mental health profiles of individuals in the similar or dissimilar subgroups can be compared. If all the members in the same group exhibit the anxiety symptoms lasting a certain time, it can be attributed that the individual's anxiety is likely to be caused by the external environment according to Kelley's attribution theory in which the cause of psychological or behavioral phenomenon can be analyzed from the perspectives of time, person and entity (Kelley 1973). For example, if each member in the dormitory A has decreased the mental health levels due to the dormitory conflict, the data panel will find out that mental health levels in dormitory A differ from that of dormitory B, and indicate that some external detrimental events happen in dormitory A rather than in dormitory B.

Therefore, the group-based dynamic panel for comparison of mental health data will facilitate the timely detection of mental health issues for college students in dormitory A.

When building a dynamic data panel based on group, it is available to dynamically display the psychological test data for different individuals in similar groups, and further compare individuals' mental health in the same group with other groups in the forms of class, dormitory, grade, campus or even community. It's also feasible to construct weight matrix by applying horizontal data and figure out the eigen-vector to represent the evolution result of mental health based on Perron-Frobenius principle. Anyway, the attribution of group difference helps to deeply understand how the external incentives or internal traits influence their mental health levels.

In contrast to group-based data panel, the dynamic panel for vertical data comparison is essentially an exhibition that depicts individual's ability to adapt to the environment and the growth curve of mental health over time, so it can be called a time-based dynamic data panel. The dynamic data panel based on time can help analyze individual's psychological adjustment ability and identify the internal reason for the moodiness.

In sum, this study proposes two types of dynamic data panel corresponding to the panel data model which advocates combining cross-sectional data with time-series data (Hu 2010). One is dynamic data panel based on group, the other is dynamic data panel based on time. Through the importation of Pyecharts library in Python, a dynamic data panel can be built up to display students' mental health in an interactive manner so as to classify and archive students' personal mental health levels efficiently.

PyEcharts is a third-party extension library for Python and a JS class library for generating Echarts charts. With a small amount of code, various Echarts style charts can be quickly generated, making it a common solution for data visualization in the era of big data (Zhang 2020). Psychological counselors can use these dynamic data panels to simulate and display the psychological evaluation data in their own way (The related code to construct horizontal data panel and vertical data panel is available by asking correspondent author on reasonable request).

Discussion

This study proposes two sources of data including horizontal data and vertical data constructing different data panels. The dynamic data panels can be constructed in accordance with the types of mental health data, that is, the group-based data panel set by horizontal data or the time-based data panel set by the vertical data. Group-based data panel sourcing from horizontal data can exhibit group's recent mental state. In contrast, time-based data panel sourcing from vertical data can help outline the fluctuation of mental health for individual and embody subject's psychological adjustment ability.

Data panel refers to the application of an interactive interface to display the data and its corresponding analytical results. Many studies claimed that the advantages of data panel were prominent in the field of firm management, marketing, transportation, tourism (Sha et al. 2011, Ryuichi & Piet 1987), but to the best of our knowledge, few studies imply the availability and advantage of dynamic data panel in the field of educational and psychological assessment. However, due to the practical significance of data panel that can help educators and psychological counselors get a timely feedback from their students and analyze the causes of psychological phenomenon to guide the subsequent works, it is of importance to dig out the advantages of data panel and innovate the method to construct the data panel. Therefore, this study aims at clarifying the usefulness of data panel and its possible construction in the field of psychological assessment and education.

As Sha et al. (2011) have pointed out that data panel has two primary benefits in the marketing compared with cross-sectional survey data. First, data panel allows users to collect micro-level information such as when consumption occurs and what type of product is consumed in every consumption occasion; Second, data panel makes it convenient to study consumer behavior dynamics in the case of diary data panel allowing markerters to study how past behaviors affect current behavior which is useful in many marketing research contexts. It is convincing that the two advantages of data panel in the field of marketing are available for educational and psychological assessment since the category of dynamic data panel is similar.

The panel data collected at a given time is dubbed the horizontal data which reflects the group variation of mental health. However, in contrast to horizontal panel data, the other panel data is collected frequently, i.e., yearly, weekly or even daily collected data, so as to reflect individual longitudinal experience, which is called vertical data. The construction of data panel needs to combine the two panel data so as to gain a comprehensive view about the mental health for college students.

The collection of panel data is not easy especially when collecting data in a frequent way. Because of the tedious and effortful work when frequently adopting questionnaires or interviews to collect data, the inconvenience brought by data collection may block the usage of data panel though the advantages of constructing data panel are obvious. Therefore, seeking some substitutable ways to facilitate data collection is necessary.

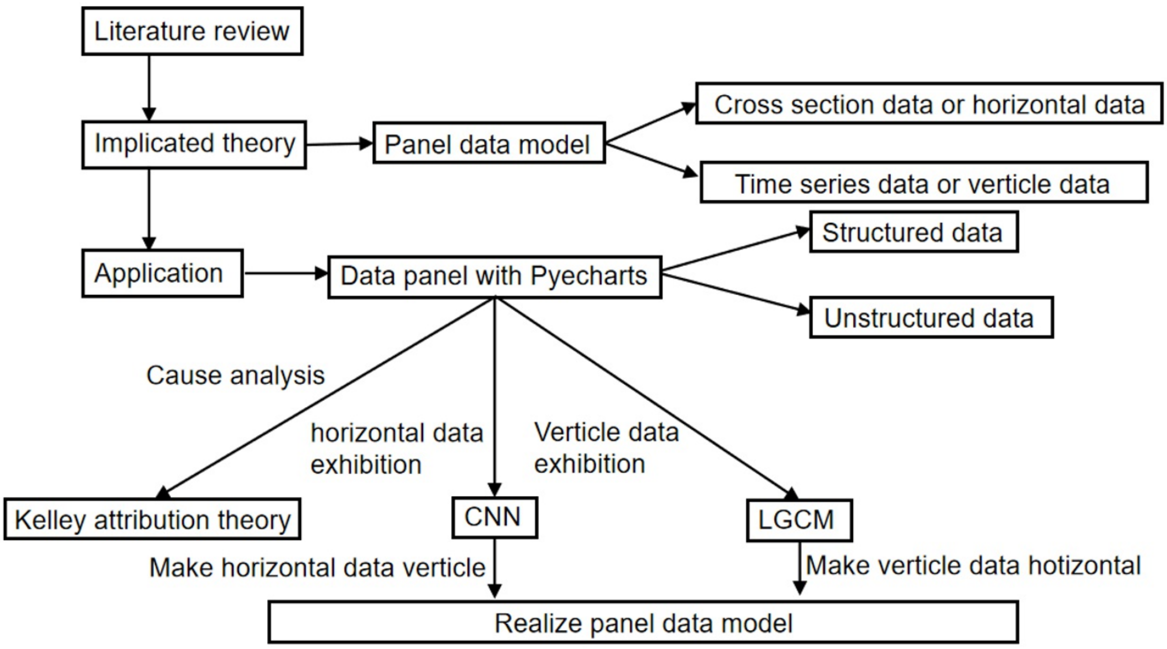

Figure 7. The research protocol for data panel with Pyecharts.

As seen in Figure 6., there are two types of panel data in the panel data model resulting in group-based data panel and time-based data panel. Each of them has the possibility to integrate and complement each other. In other words, group-based data panel merely compares psychological test data by groups but cannot show individual's mental health trajectory in the timeline. Nevertheless, time-based data panel only shows the fluctuation of mental health for individual along the timeline but can not make comparison between groups. Therefore, it's recommended to integrate the two panel data to show the whole picture of mental health for either individual or group and give the insight about the causes of psychological or behavioral phenomenon depending on Kelley's attribution theory. Meanwhile, the inconvenience of data collection for constructing data panel may be solved due to the advent of machine learning and artificial neuron network such as Random Forest, Supportive Vector Machine (SVM), ensemble learning, deep neuron network (DNN) and convolution neuron network (CNN), etc., these advanced algorithms exert great advantage on object prediction and classification especially when the data is unstructured as in the forms of video tape, image pixel, sound data, audiovisual files, web-based platforms, etc. (Chen et al. 2020).

Conclusion

The innovation of this article is that it proposes a new way to combine the test result from different scales. That is, K-Means cluster model in machine learning can be adopted to melt the test result of SCL-90 into that of UPI so as to realize the combined test of short-term mental state and long-term psychological adjustment ability, and make the psychological assessment comprehensive.

Moreover, the other way to integrate mental state into psychological adjustment ability is through data panel. The study proposes two schemes for designing dynamic data panels for mental health assessment, namely, group-based data panel and time-based data panel. Time-based data panel reflects individual's psychological adjustment ability and the growth curves of mental health at different point of time. When individual's psychological adjustment ability is strong, the time-based data panel will show the obvious rebound from emotional trough and the increased mental health levels over time, and vise verse.

The dynamic data panel based on group can identify the environmental factors for the change of mental health and reveal the reason for such a change according to Kelley's attribution theory, for example, group-based data panel is available to compare the average mental health levels in dormitory A with other dormitories and discover the worsening psychological state in dormitory A is due to the daily schedule conflicts and misunderstandings among dormitory members according to the person and time angle in Kelley's attribution theory.

It is worth noting that although data panel has plenty of advantages, emphasis should be placed on the confidentiality of psychological assessment and the degree of acceptance of the data panel by the participants. According to the confidentiality principle of psychological assessment, the psychological data panel can only be opened to a small number of people as least as possible, such as the subjects and their parents, counselors and their leaders, clinicians, etc. (Song & Li 1998). Users can only maximize the advantages of data panel on the basis of following the confidentiality principle.

In conclusion, the establishment of the dynamic data panel provides a dynamic data monitoring platform and vital information for psychological counselors and educators, and facilitates the establishment of mental health archives. Dynamic data panel may give assistance to the follow-up psychological counseling and help counselors deeply understand the reason for the fluctuation of mental health for individual. Thus, it deserves advocating and extending its usage in universities.

Conflict of Interest

The authors declare no conflict of interest.

References

- Chen L, Chen P & Lin Z: Artificial intelligence in education: a review. IEEE Access.2020; 8, 75264-75278.
- Florencio F, et al: Performance analysis of deep learning libraries: tensor flow and pytorch. J comput sci 2019; 15: 785-799.
- Geiser C: Data Analysis with Mplus. Guilford Press, New York, 2012;
- Kelley HH: The processes of causal attribution. Am Psychol, 1973; 28: 107.https://doi.org/10.1037/h0034225.
- Giovanni B: Artificial intelligence in psychiatry. Psychiatr Danub 2023; 35: 15-19.
- Kieffer KM. Why Generalizability Theory is Essential and Classical Test Theory is Often Inadequate? New Orleans, LA:

USA. 1998.

- Lin J: The combination of the Personality Questionnaire for College Students and the Symptom Checklist was used in the psychological survey of college freshmen. China J Health Psychol 2007; 15: 45-46.
- Mahadevkar SV, et al: A Review on Machine Learning Styles in Computer Vision—Techniques and Future Directions. IEEE Access, 2022; 10: 107293-107329. https://doi.org/10.1109/ACCESS.2022.3209825.
- Patricia S, et al: The association of intrapersonal trait emotional intelligence and resilience with suicidal ideation in university students. Psychiatr Danub 2021; 33: 298-305.
- Ryuichi K, Piet HLB: Analysis of attrition biases and trip reporting errors for panel data. Transportation Research Part A: General, 1987; 21: 297-302.
- Sha Y, Yi Z & Dhar R: Modeling the underreporting bias in panel survey data. Soc Sci Electronic Publishing 2011; 29: 525-539.
- Shan MH: Correct use of SCL-90 and 16PF scales to measure mental health. Chin J Ment Health 1998: 12:81-82.
- Shen XQ, et al: Research on the Relevance Alternative and Complementary of UPI and SCL-90. Value Engineering 2010: 29: 112-113.
- Shi LY, et al: Evaluation of reference values, reliability, and validity of the SCL-90 scale used by college students. Chin J School Health 2013; 34: 223-224.
- Song XH, Li JM: Exploration on the Experience of Psychological Testing. Chin J Health Psychol 1998: 6: 45. https://doi.org/10.13342/j.cnki.cjhp.1998.s1.042.
- Tan Z, Mun EY, Nguyen USDT, et al: Increases in social support co-occur with decreases in depressive symptoms and substance use problems among adults in permanent supportive housing: an 18-month longitudinal study. BMC Psychol, 2021; https://doi.org/10.1186/s40359-020-00507-0.
- Wang D, Nan JKM & Zhang R, Structured group sandplay to improve the resilience of college students: A pilot study. Art Psychother 2017; 55: 186-194.
- Wang JA: comparative study of UPI and SCL-90 in psychological measurement of Freshmen. Youth and Adolescent Studies 2019;2: 39-42.
- Wang JZ: Comparative study of UPI and SCL-90. Chin J Ment Health 1995; 3: 437-439.
- Wang MJ, Wang YY: The Use of UPI and SCL-90 in Psychological Surveys among College Freshmen, J Lishui Univ 2020; 42: 124-128.
- Yang SL, Li YS, Hu XX, et al: Optimization Study on k Value of Kmeans Algorithm. Syst Engin -Theory & Practice, 2006; 26:97-101.
- Yu N: Discussion of public mental health problems based on intelligent data analysis technology under the background of the COVID-19 pandemic. Psychiatr Danub 2023; 35: 239-244.
- Zhang YY: Data visualization based on PyEcharts. Comp Knowl Technol: Academic Exchange 2022; 18: 24-27.
- Hu J, et al: The application status and development trends of panel data models. Stat decis 2010; 17: 21-24.
- Zhang J, Zhang XG, Chinese college students' SCL-90 scores and their relations to the college performance. Asian J Psychiatr 2013; 6: 134-140.