Is Data Panel Beneficial for Mental Health Assessment? Application of Pyecharts Library

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

1 Guangzhou Huashang Vocational College

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Abstract

Symptom Checklist 90 (SCL-90) and University Student Personality Inventory (UPI) are commonly used mental health scales for college students. SCL-90 reflects individual psychological 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, the current psychological test results in universities are mainly presented in the form of static cross-sectional images, lacking a dynamic visual platform and user interaction interface. Based on the test data from college freshmen by means of SCL-90 and UPI, this study uses Pyecharts library in Python to build a dynamic mental health data panel, and presents static mental health data in an interactive interface in which Kelley's attribution theory is used to judge the causes of mental health problems. Meanwhile, latent growth curve model (LGCM) can be applied in time-based data panel and convolution neuron network (CNN) may be deployed in group-based data panel with a view to scientifically managing mental health data and effectively detecting the change of mental health levels, therefore timely providing intervention basis for follow-up psychological consultation and education.

Yuan Guofan[1], **Li Xiong**[2] and **Wang Huiqiu**[1,*]

[1] *Guangzhou Huashang Vocational College, Guangzhou, 511300, Guangdong, China;* ygf7852@163.com

[2] *Mental Health Education and Consultation Center, Guangzhou Huashang Vocational College (Xinhui district), Jiangmen, 529100, Guangdong, China;* 1173321980@qq.com

[*] *Correspondence:* dragon105@163.com

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1. Introduction

The Symptom Check List (SCL-90) and the University Personality Inventory (UPI), which are commonly viewed as the effective mental health screening tools, are able to provide reliable testing results for psychological assessment of college students due to their good-fit indexes in the framework of 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 related studies. The measured results from SCL-90 and UPI have certain clinical practical significance, therefore being widely adopted for mental health measurement (Shi, 2013; Wang, 1995).

The combination of the measurement results from SCL-90 and 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 organically and jointly in testing and intervention work for the improvement of mental health levels of 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 mental health rather than the single scale test, testers not only can judge the severeness of mental health by the classification of UPI that relies on national norm, but also analyze the specific positive symptoms exhibited by subjects in SCL-90 measurement; On the other hand, combined test is more able to embody the conception of mental health and is more comprehensive than the single scale test which adopts only one scale for testing. Combined test constellates more constituent facets of mental health such as positive emotional state, good traits for adaptation, and strong mental adjustment ability, whereas single scale test only reflects some aspects of them.

Combined test of UPI and SCL-90 is equivalent to integrating test of unstable and temporary psychological state into test of stable and long-term psychological adjustment ability, therefore, combined test makes 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, psychological state and mental adjustment ability. SCL-90 tests mental health problems in a very short period about one week. In this sense, SCL-90 merely reflects the recent psychological states of college students, while UPI tests the mental health problems over a longer period about one year, therefore, the trait for adaptation and the mental adjustment ability are reflected in UPI measurement.

The two scales can be integrated together to reflect the overall picture of mental health. Therefore, many universities give priority to the combined test using the two scales when conducting psychological surveys and screening mental health issues for college freshmen. As one case of screening mental health issues for college freshmen using the combined test, the combination of measurement results of SCL-90 and UPI can be analyzed by K-means cluster model as seen in Figure 1.

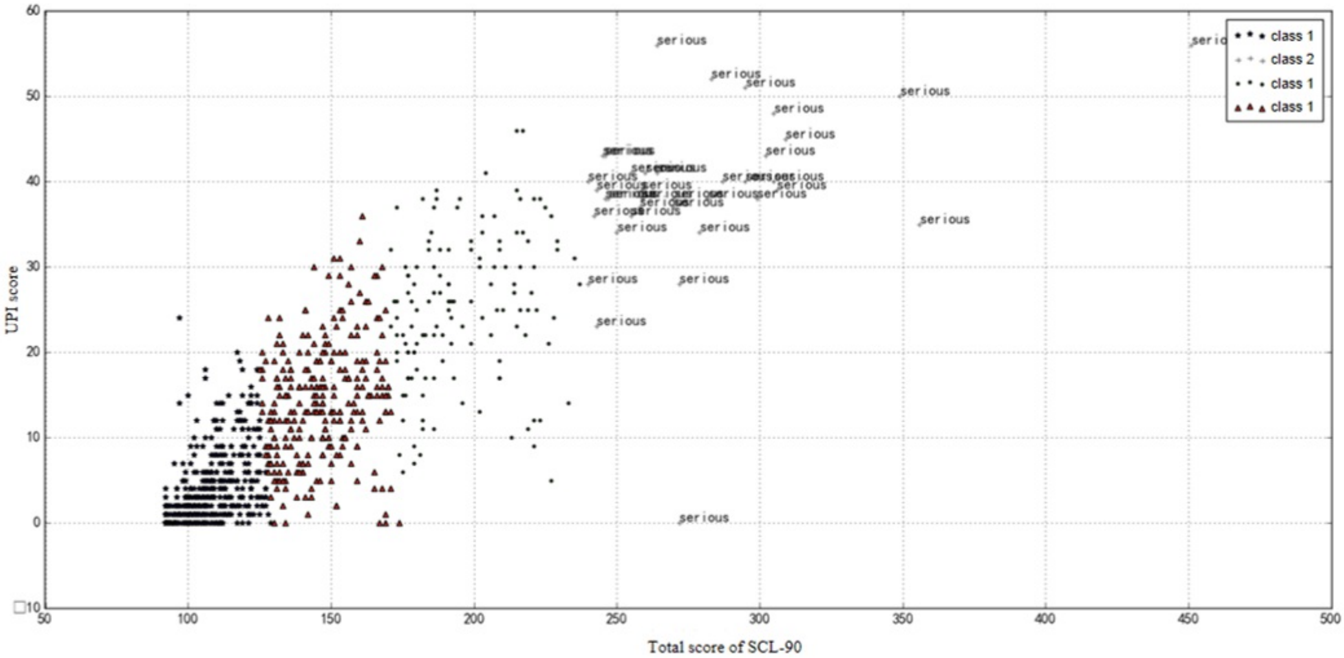

Figure 1. K-means cluster model combined the testing result of SCL-90 with UPI.

The data shown in Figure 1 was derived from a sample of 920 college freshmen. Every symptom score in SCL-90 and total score of UPI are taken consideration in the cluster model using Euclidean distance to acquire optimal class (Yang, et al., 2006). Due to the anonymity and privacy for study protocol declared in Helsinki (Li, et al., 2022), the screened-out name list of college students is replaced by the “serious” label in Figure 1 and the charted data is therefore merely a showcase for the testing results.

The K-means cluster model is the unsupervised classification model where K representing the number of classes is free to set. Individuals with severe psychological health issues can be figured out from the cluster model in which k value is assumed to be 4 theoretically ranging from the worst mental health class to healthy class with both high score of SCL-90 and UPI as indicators of mental health seriousness (Wang & Wang, 2020). The K-means classification model informs psychological counselors and educators about the listed students to whom they should pay attention.

The relevant departments in university can collect students' psychological health data through SCL-90 and UPI, and screen individuals with psychological problems based on gold standard or national norm, ultimately identifying the population with psychological health problems or positive 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 a norm-based psychological questionnaires 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 testing is usually regarded as a part of intake interview in psychological counseling, and its contribution to the psychological assessment is limited. It is generally filed after the evaluation is completed, so the quantitative data obtained through psychological testing is easily ignored and has a low utilization rate. For instance, for individual without psychological symptoms, the results obtained through psychological test may manifest positive 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 error, that is, there are false positive symptoms and type I error existing in the test. In order to avoid misjudgment of the actual situation and reduce the incidence of type I error and type II error, psychological counselor often needs to use in-person interviews as the final basis for psychological evaluation, and psychological testing is just one way to assist evaluation. Psychological test can only stay in the position of auxiliary evaluation and reference, and does not determine the final evaluation results. Therefore, the data obtained through psychological testing will subsequently be archived after the evaluation is finished, 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 counseling process, they no longer use the psychological test results as a reference basis. Instead, they pay more attention to the evaluation results obtained from psychological interviews than the quantitative test data. This approach has its rationality, but it is easy to overlook the full use of psychological test data, ignoring the possibility of distilling causes of personal behaviors through horizontal and vertical comparison of psychological test data which has not fully exerted its potential value.

2. Horizontal comparison of test data

The full exploration on the potential value of psychological test is proportional to 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 inter-group level at a given time, whereas the vertical comparison of psychological test data is a comparison of individual historical data accumulated in a daily or weekly way and spanning a certain length of time.

The horizontal comparison helps to detect individual or group difference. By the comparison of mental health levels of individuals or groups from horizontal data, group or individual difference can be detected in time so as to intervene extreme behaviors such as hurting oneself or behaving problematically, and that indirectly reveal the external detrimental factors related to the worsening mental health levels such as life events. In addition, if combining with convolution neuron network (CNN) in the field of artificial intelligence (AI), the horizontal data can be treated like vertical data and being constantly flowed into the AI model to provide more accurate prediction for the causes of the worsening mental health levels based on the training of historical data from the campus surveillance system if technically available and legitimately possible.

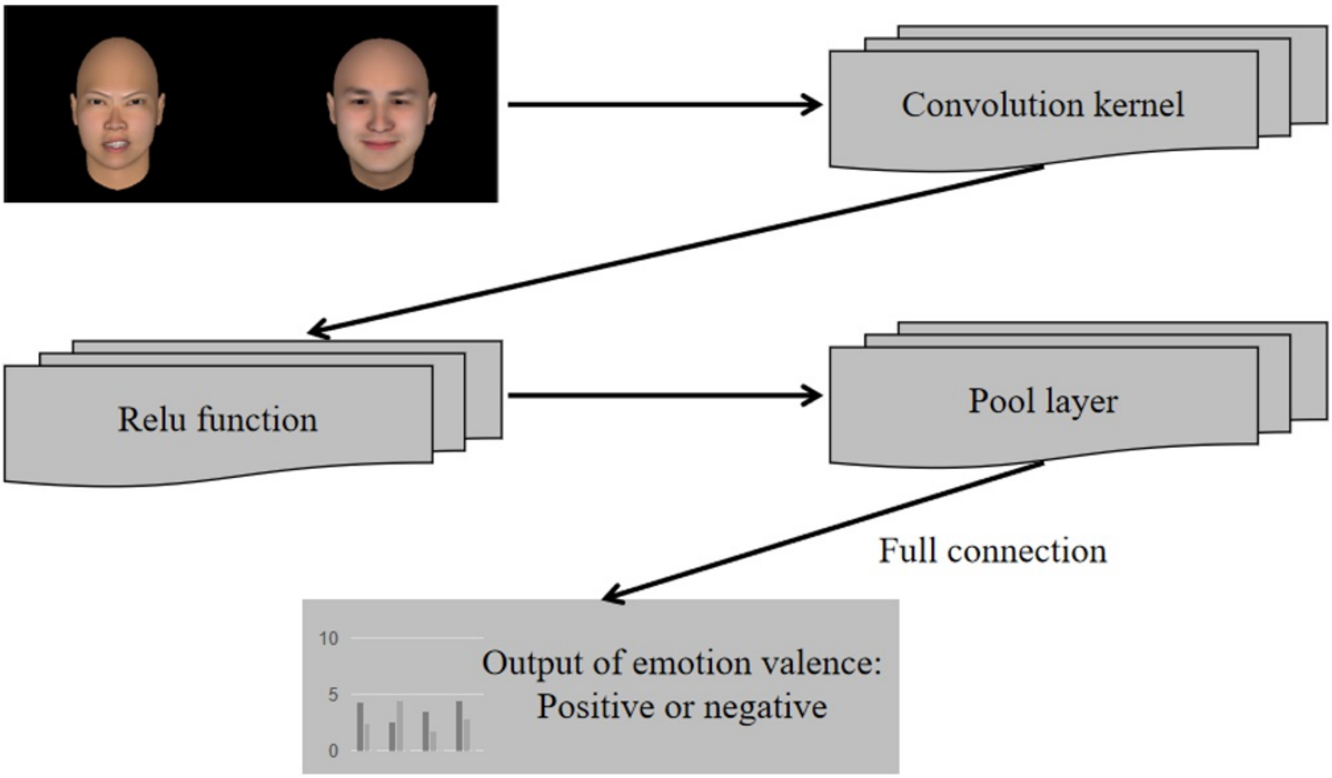

Figure 2. Application of CNN for recording students' emotional statuses.

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

The feasibility of using CNN to trace the psychological status 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 2, a convolution neuron network can be built to effectively recognize the facial emotion valence and record college students' daily mental health over time to overcome the insufficiency of horizontal data comparison based on group for its inability to trace individual mental health trajectory during different period.

In a case to elucidate the usefulness of horizontal data comparison, comparison by group can be refined to the dormitory. College students in the same dormitory often share the common ground in terms of mental health because of the mutual influence between each of them, which is displayed through a dynamic data panel based on dormitories. Psychological counselors have noticed that everyone in the same dormitory has a low level of mental health compared to other dormitories. Through further interviews, it has been found that the the referent dormitory has serious interpersonal conflicts caused by the distinct living habits among the dormitory members, further measures can then be taken in relieving the dormitory conflicts, e.g., counseling this kind of problems by the approach of Rational-Emotive Therapy or CBT for the involved members. The dynamic data panel based on dormitory 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.

Horizontal comparisons include both comparisons between individual and norms, and comparisons between different group. Norm comparison is a comparison between normative data and individual score. Although norm comparison is scientific and conclusive which is called gold standard for judging if the seriousness of subject's symptoms exceeds most people, this comparison can neither reflect group difference, nor can it explain why the referent group experiences such a change. For example, comparing individual's anxiety symptom in SCL-90 with normative score can determine whether or not the individual exceeds the average anxiety level of most people, but it is neither easy to know the anxiety difference within various subgroups, nor that to disclose the reasons for such a change of anxiety levels in the dormitory, class or community.

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 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). In the case mentioned above, if nearly every member in the dormitory A performed the decreased mental health levels due to the dormitory conflict, the data panel will show that the mental health in dormitory A differ from that of dormitory B, and indicate some external detrimental events happen in dormitory A rather than in dormitory B. Therefore, group-based dynamic panel will facilitate the timely detection of mental health issues for college students.

3. Vertical comparison of test data

The vertical comparison is a comparison of personal longitudinal experience across time and a comparison of psychological test data 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 if existed 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 once a time 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 shows the curve of mental health fluctuation for individual. Besides, the time-based data panel can also compare different growth curves of mental health within distinct groups by combining with the latent growth curve modal (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 3, the decrease of the red line demonstrates the upward trend of group’s average mental health levels). The time-based panel will provide the representative information of groups when combining with LGCM with auto-regressive effect retrieved.

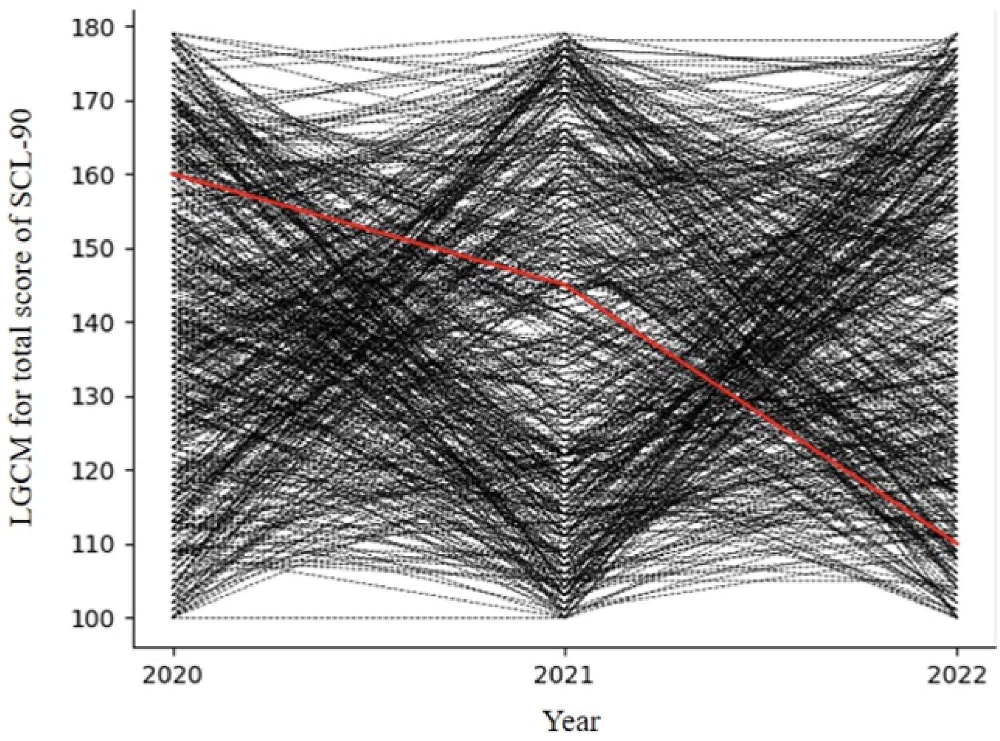

Figure 3. Latent growth curve model (LGCM) for vertical data collected by SCL-90.

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 change trend of characteristics of the sample (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 but that capable of comparing recent personal experience with past experience.

4. Dynamic data panel construction

The establishment of a dynamic panel provides an effective solution for horizontal and vertical comparison of psychological test data. The dynamic panel for horizontal comparison of test data is essentially an exhibition of comparison of similar or dissimilar groups, so it can be called a group-based dynamic data panel.

When building a dynamic data panel based on group, it is possible to dynamically display the psychological test data for different individuals in similar groups, so as to compare individuals' mental health in the same group with other groups in the forms of class, dormitory, grade, campus or even community. 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 comparison of mental health data 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 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, 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 charts. With a small amount of code, various Echart-style charts can be generated, making it an usual solution for data visualization in the era of big data (Zhang, 2020). This article uses the dynamic data panel to display the psychological evaluation data for college freshmen. Through bar charts, dashboards, word clouds, Nightingale rose charts, and water drop charts, the dynamic data panel based on group or based on time were presented.

5. Two types of data panel

5.1. Group-based dynamic data panel

When constructing a group-based mental health data panel, it is necessary to import the Pyecharts library for drawing bar charts, dashboards, word clouds, and Nightingale rose charts.The code running results are shown in Figure 4.

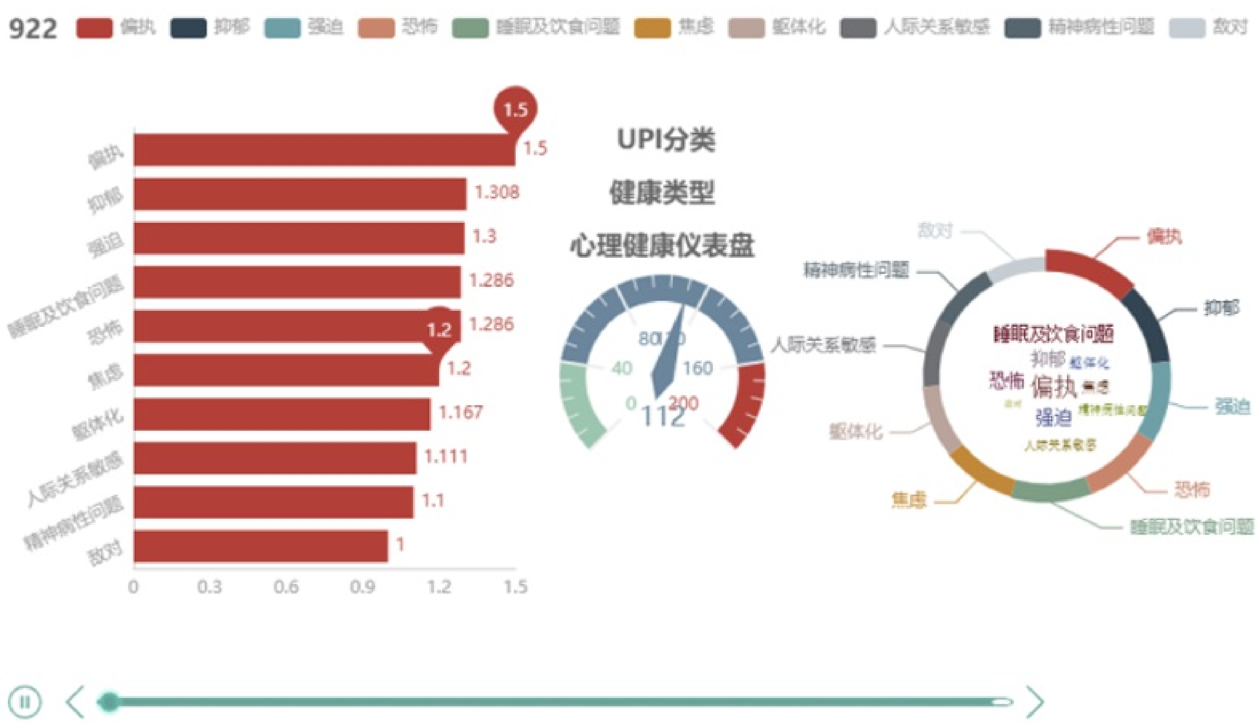

Figure 4. Data panel of mental health based on group.

The data panel is dynamically displayed by switching between different individuals and subgroups. The current image shows the evaluation result of an individual grouped by class. The bar chart on the left shows SCL-90 factor scores, and a score greater than 2 indicates a positive symptom. The bar chart is sorted from top to bottom based on the factor score in SCL-90. The middle section in the form of text is the UPI classification result. According to the UPI diagnostic criteria, those who score 25 or above, or those who make a positive choice on the 25th question, are the most severe type with mental health issues exhibited, followed by the less severe type scoring between 20-24; The type scoring below 20 is defined as mentally healthy type.

The instrument panel on the middle side is a total score of SCL-90. When the pointer in the instrument panel points to the red area, the individual has the poorest mental health level; On the right side of the data panel is a word cloud analysis of the symptom. The larger the font size, the serious the symptom. At the same time, the circular arc shape in the outer circle is a Nightingale rose chart. Moving the mouse over the area will display the numerical value of the area (Zhang, 2020). As shown in Figure 4, the individual has dietary and sleep problems, so it is recommended that the individual should adjust the work and rest schedules, eat regularly, and cultivate a healthy living habit.

5.2. Time-based dynamic data panel

Importing the Liquid module from Pyecharts library to dynamically display the evaluation data collecting from different years, months or weeks which is called time series data or vertical data. Time-based data panel can be set up based on this kind of data.The code run results are shown in Figure 5.

Figure 5. Data panel of mental health based on time.

Pyecharts module is applied to build a water droplet diagram that moves continuously. The water drop chart shows that the total score of SCL-90 for individual was 160, 145 respectively in the year of 2020 and 2021. By 2022, the total score of the SCL-90 was 110 with 200 as the total score. The three-year scores accounted for 80%, 72.5%, and 55% of the total score, respectively. A water drop chart can intuitively show the change of mental health over time. The lower the SCL-90 score, the higher the level of mental health. The mental health panel shows that the individual's SCL-90 score has decreased over the past three years, manifesting an upward trend of mental health which may result from the fear dissipation of Covid-19.

The period from 2021 to 2022 is characterized with the largest drop in the water level, indicating the fastest rise of mental health levels and strong resilience to recover from Covid-19. Enlightened by the time-based data panel, the specific reasons for the change can be explored through group-based mental health data panel or clinical interviews based on Kelley's attribution theory.

6. The advantages of constructing data panel

This study proposes that there are two sources of data including horizontal data and vertical data helping construct different data panels. The dynamic data panels can be built 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 psychological state. In contrast, time-based data panel sourcing from vertical data can help outline the fluctuation of mental health and embody subject's psychological adjustment ability.

Data panel refers to the application of an interactive interface to display the data and its corresponding analytic 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, extremely few studies imply the availability and advantage of dynamic data panel in the field of education 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 cause of psychological phenomenon to guide the subsequent works, it is of importance to discuss 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 education and psychological assessment since the procedure of constructing data panel is similar.

The panel data collected at a given time is dubbed the horizontal data which reflects the group difference 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 can be completed based on the two panel data so as to gain a comprehensive view about the mental health for college students.

However, 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.

7. The method to construct data panel

As mentioned above, there are two types of data panel in the practical work, that is, group-based data panel and time-based data panel. Each of them has the possibility to integrate and complement each other by conquering their respective drawbacks. In other words, group-based data panel can compare psychological test data by groups but cannot show the mental health trajectory in the time line. However, time-based data panel can show the fluctuation of mental health for individual along the timeline while cannot make comparison between groups. Therefore, it’s recommended to integrate the two data panel to show the whole picture of mental health for either individual or group and give 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 have great advantage on object prediction and classification especially when the data is not well configured as in the form of video tape, image pixel, sound data, audiovisual files, web-based platforms, etc. (Chen, et al., 2020).

Moreover, the scientific data analysis process set in the data panel helps to effectively detect mental health issues. As discussed previously, the method to construct data panel depends on two distinct data (i.e., horizontal data versus vertical data) leading to group-based data panel and time-based data panel. Group-based data panel can detect group difference such as dormitory conflict at a given time but can not show individual's journey of mind over time. Time-based data panel can exhibit individual's mental health over time, but can not compare group difference of mental health. In order to eradicate the time limit in group-based data panel, convolution neuron network in the field of AI may be trained with the data either sourcing from psychological assessment or from campus surveillance system with video record in public. At the same time, latent growth curve model can be adopted in time-based data panel in order to exhibit the representative trend of mental health levels in samples and subgroups with only vertical data presented.

By employing the convolution neuron network to analyze video data from campus surveillance system at school, student's daily emotion status can be recorded in the data panel. Meanwhile, the adoption of video tape makes data collection convenient. In addition, by applying latent growth curve model, representative growth curves of mental health among different subgroups can be compared. However, it should be cautious that when applying data panel, privacy and legitimacy issues should be noticed if campus surveillance system were involved.

8. Conclusions

The innovation of this article is that it proposes two schemes for designing dynamic data panels for mental health assessment through Pyecharts library, namely, a group-based data panel scheme and a time-based data panel scheme. Time-based data panel can reflect 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 increase of mental health levels over time, and vise verse.

The dynamic data panel based on group can identify the environmental incentives for the changes of mental health and reveal the reason for these changes, 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, 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 school counselors and educators, and facilitates the establishment of mental health archives. Dynamic data panel may give assistance to the follow-up psychological counseling work and help counselors deeply understand the reason for the fluctuation of mental health for individual. Thus, it deserves advocating and extending the mixed usage of group-based data panel and time-based data panels in psychological education and consultation centers in universities.

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