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Emotional Management and Mental Health Promotion in Young Children: An Empirical Study of Educational Intervention

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A R T I C L E   I N F O

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A B S T R A C T

Aim: Emotional Regulation and Mental Health Enhancement in Early Childhood: An Empirical Examination of Educational Interventions. **Methods:** The study involved a group of 210 students, with 100 participants assigned to the intervention group and another 100 assigned to the control group. 200 individuals successfully completed their participation in the research study. A range of psychological assessment instruments, including the General Health Questionnaire (GHQ-28), the Oxford Happiness Questionnaire, Sherer's General Self-Efficacy Scale, Cohen's Perceived Stress Scale, Snyder's Hopefulness Scale, and Diener's Satisfaction with Life Scale (SWLS), were utilised in Persian adaptations to evaluate various aspects of well-being. **Results:** After conducting a thorough analysis comparing groups that received intervention with control groups, the findings indicate that there were no significant changes in mental health indicators except for a slightly significant correlation with a moderate level of happiness (odds ratio [OR] 1.55, 95% confidence interval) [CI] 0.89–2.59, p = 0.07). By employing a sign test and analysing pre-post-testing data, a notable change in the distribution of results between the intervention and control groups has been identified. Specifically, this alteration is discernible in the domains of life satisfaction (p < 0.001) and happiness (p < 0.001). **Conclusion:** The use of the SMHPP, known for its cost-effectiveness, focus on personalised needs, and comprehensive approach, shows potential for promoting mental well-being among young people. Public health authorities are encouraged to support and promote effective initiatives, especially in poor countries where resources for mental health interventions in schools are often scarce.

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Introduction

The prevalence of psychological challenges among university students, encompassing issues such as suicides, criminal activities, and other adverse incidents, is on the rise, indicating a sustained upward trajectory over an extended period. This trend has impeded the operational effectiveness of higher education institutions, hindered the personal development of college students and their families, and disrupted societal equilibrium. Consequently, the psychological challenges encountered by college students have garnered considerable attention from various segments of society. A psychological crisis is characterised as a transient state of psychological instability with the potential to cause substantial harm to oneself, others, or society. College students frequently confront significant psychological challenges that can profoundly impact their academic performance and overall mental well-being, leading to a variety of unfavourable outcomes.

The ongoing pandemic has prompted a notable surge in research endeavours within the realm of health analysis. The enforcement of stringent isolation measures has engendered apprehensions regarding the mental well-being of students. To address this concern, numerous educational institutions have instituted health committees aimed at assisting students in maintaining their physical health. Additionally, these institutions have established information support departments to fulfil the informational needs of students more effectively. This study delves into the impact of supportive interventions on the psychological well-being of students, utilising data obtained from a survey specifically focused on ideological education within a social context.

Scholarly consensus underscores the efficacy of college students in effectively addressing and managing psychological crises. Higher education institutions commonly employ two distinctive strategies for handling psychological crises. The first approach concentrates on offering general education courses designed to equip students with the requisite skills to foster and sustain optimal psychological well-being. The second approach centres on the identification of students' psychological issues through reporting mechanisms, measurement scales, psychological therapy, and other pertinent methodologies. Subsequently, targeted preventive measures are instituted to mitigate the occurrence of crises.

An alternative strategy involves leveraging psychological crisis indicators to enhance the proactive prediction of psychological crises. Effectively managing mental health crises among university students necessitates the precise identification of individuals grappling with mental health challenges and the implementation of appropriate levels of intervention and surveillance. Presently, numerous universities in China lack standardised and comprehensive techniques for warning students about psychological crises. The existing body of academic research pertaining to the identification of psychiatric emergencies among university students primarily comprises theoretical frameworks, with a paucity of practical methodologies. Additionally, the commonly used psychological crisis screening method, which is called "statistical analysis based on the clinical diagnostic scale," has several problems, such as inaccurate measurements, reliance on a single indicator, limited effectiveness, and lateness. Consequently, it is imperative to devise a practical and evidence-based psychological emergency notification system for college students to address these issues (Cull & Gill, 1982; Gebhard, 2005).

Social media platforms, coupled with big data technology, offer innovative avenues for addressing these challenges. Currently, social media stands as the predominant platform through which college students share their experiences, articulate opinions, disseminate information, and provide insights into the real-life encounters of their peers within the collegiate environment. Leveraging precise and contemporary samples of social media big data introduces novel possibilities for refining methodologies aimed at identifying psychiatric crises among college students.

Big data technology facilitates the systematic collection of daily behavioural data from college students active on social media platforms. This information can be subjected to analysis to glean insights into their psychological states and characteristics. Ongoing research endeavours enable the swift identification of mental health vulnerabilities, facilitating timely recognition and intervention in psychological emergencies among college students. This study employs a comprehensive analysis of extensive and current social media data to construct a framework for the detection of psychological emergencies. The investigation involves the creation of relevant algorithms, followed by simulation experiments, and is based on stress response theory and personality theory in the field of psychology. The overarching goal is to provide a thorough examination of how big data can be employed to detect psychological emergencies among university students at an early stage (Hamilton, 1959).

Review of Literature

When examining the technical development of alerting college students to psychological crises, it is possible to categorise the methodologies into three distinct categories: There are three different approaches to warning systems: traditional methods, information system-supported methods, and big data-supported methods.

Traditional Warning Methods

The assessment of psychological crises typically employs a statistical analytic methodology characterised by the application of a clinical diagnostic scale. This approach centres on identifying early warning signs based on psychological theories, culminating in the development of a scale. Subsequently, students are directed to complete the scale actively or passively. Utilising statistical analytic techniques enables the evaluation of students' psychological crisis states based on the collected data. Various metrics have been devised to assess distinct classifications of states undergoing crises.

Prominent tools for appraising suicidal thoughts encompass the Scale for Suicide Thoughts (SSIC), the Adult Suicidal Ideation Questionnaire (ASIQ), and the Suicide Probability Scale (SPS). Regarding the evaluation of depression symptoms, widely employed tools include the Symptom Checklist 90 (SCL-90) and the Hamilton Depression Scale (HAMD), among other available options. Several commonly utilised measures assess and quantify symptoms of anxiety, such as the Self-Rating Anxiety Scale (SAS), the State-Trait Anxiety Inventory (STAI), and the Hamilton Anxiety Scale (HAMA).

In the initial stages of psychological crisis screening, data for statistical analysis predominantly relied on paper-based questionnaire surveys. The surveys mostly produced static and experimental data, which had a lot of problems, such as big measurement errors, relying too much on one indicator, being less efficient, and not being up to date enough (Holmes & Rahe, 1967).

The Use of Information Systems to Facilitate the Process of Issuing Warning

The pervasive integration of digitally intelligent cloud platforms, coupled with continuous advancements in computers, the Internet, and other information technologies, has significantly influenced university administration across various dimensions. Consequently, the adoption of information systems for early warning has emerged as a prevalent approach to effectively managing psychological crises in university settings.

The Expert Steering Committee of Students' Mental Health Education in Colleges and Universities under the Ministry of Education developed the "Chinese College Students Mental Health Assessment System," which serves as an example in this field. Furthermore, numerous universities have autonomously crafted mental health survey platforms for college students based on experiments conducted by diverse higher education institutions.

The deployment of these technologies in conducting psychological surveys among college students seeks to overcome the limitations associated with traditional paper-and-pencil psychological assessments. These constraints encompass inefficiencies related to time, heightened demands on effort, compromised statistical accuracy, and delayed information retrieval.

Nevertheless, the psychological census often relies on screening questions, which can induce reluctance among college students to self-identify as having psychological issues. Consequently, some students may opt not to provide accurate information, leading to resistance during the psychological census and, ultimately, the generation of inaccurate results. In conjunction with the use of psychological survey systems, many colleges and universities deploy student information management systems. These systems employ diverse methods, including online consultation platforms and offline screening channels, to actively monitor students' engagement in enhancing psychological management.

Student information management systems leverage data collected from students participating in psychological stress censuses conducted throughout the academic year, mitigating the limitations associated with relying solely on one source of psychological information. Despite their enhanced accuracy and efficiency compared to traditional paper-and-pencil psychological examinations, many current systems are confined to objectively documenting students' mental health indicators. Data processing primarily revolves around fundamental statistical analysis, access control, data backup, and retrieval, resulting in the underutilization of the vast potential inherent in the data (Iwendi et al., 2020).

Stress Response Theory

A psychological crisis denotes an individual's psychological reaction to challenges that exceed their ability to cope effectively with internal and external pressures using conventional methods. Acute stress reactions often manifest when confronted with an inevitable and highly distressing event, perceived as a potential threat to one's well-being and safety, following a thorough assessment. Once traditional coping mechanisms are depleted, individuals encounter notable short-term difficulties in emotional, cognitive, and behavioural functioning.

The stress events under discussion, commonly termed life events, constitute external stimuli capable of eliciting stress reactions. These stress events can be categorised into four primary types: physical, psychological, cultural, and social. Somatic events specifically pertain to incidents directly impacting an individual's physical body, resulting in observable manifestations of stress.

These incidents may encompass elevated temperatures, instances of illness, or acts of physical aggression towards individuals. Psychological events involve stress-inducing situations arising from internal conflicts, such as the pressure to meet high expectations in an exam. Cultural events entail challenges related to adapting to a new lifestyle and religious practices, as observed in the process of studying abroad. Social events encompass psychological stress arising from events within the social sphere, such as disruptions in society and conflicts between individuals.

In their seminal work, Folkman (1984) categorised stress responses into three dimensions: physiological, psychological, and behavioural reactions. Psychological responses often encompass both emotional and cognitive aspects. A person's emotional formation becomes an adult due to experience and knowledge gained in childhood so it shows positive emotions and negative emotions (Suryana & Latifa, 2023). Common emotional responses include feelings of concern, fear, depression, and anger, among others. Typical cognitive responses may involve feelings of paranoia, persistent overthinking, refusal to accept, and selective forgetfulness. Physiological responses refer to changes in physiological indicators, such as blood pressure and respiration, in response to stress-inducing stimuli. Behavioural responses often manifest as a range of emotions, including avoidance, regression, anger, and self-pity, among other possible expressions.

When confronted with a stressful event, a distinctive physiological response is triggered, as elucidated by the stress response step model introduced by Horowitz et al. (1996), as depicted in Figure 1. The stress response process is conventionally delineated into five discernible phases: scream, denial, invasion, ongoing correction, and closure. From a clinical standpoint, it is widely acknowledged that the phenomena of denial and invasion represent two distinct phases. However, there exist variations in how individuals experience and manifest different stages of the stress response, encompassing differences in manifestation, intensity, and sequence.

In the denial stage, individuals may exhibit symptoms such as emotional numbing, a reluctance to acknowledge certain ideas, and behavioural constraints. The intrusive stage involves the repetitive occurrence or recollection of the distressing experience through various channels, including direct, symbolic, intellectual, or emotional means. Symptoms associated with this stage can manifest as nightmares, intrusive thoughts, or sudden emotional responses unrelated to the current situation. Prolonged or heightened activation of the stress response can lead to numerous potential negative outcomes (Lucas & Diener, 2001).

Personality Theory

Stress responses can be categorized into three dimensions: physiological, psychological, and behavioural reactions, as identified by Folkman and Lazarus (1980). External stressors act as triggers that elicit emotional responses in individuals. However, when confronted with comparable pressures, individuals deploy diverse coping mechanisms, leading to a range of emotional reactions primarily influenced by their distinct personality traits. Substantial empirical research underscores the significant impact of personality on emotional expressiveness. A clear association has been established between psychiatric crises and individual personalities. Personality traits play a pivotal role in shaping how individuals think and behave, representing an intricate interplay between the mind and body. Psychologists have proposed various models of personality, with the "Big Five" personality model being particularly well-known.

The "Big Five" personality model categorizes individuals into five distinct dimensions: openness, conscientiousness, extraversion, agreeableness, and neuroticism. Individuals with open personality traits typically exhibit qualities such as imagination, emotional sensitivity, and creativity. The conscientious personality type is characterized by an emphasis on fairness, caution, and restraint. Conversely, the extroverted personality is marked by traits like high energy, strong decision-making skills, a love for adventure, and a focus on objectivity. The agreeable personality type is often associated with qualities such as confidence, honesty, cooperation, and similar characteristics. Neurotic personality traits encompass a spectrum of psychological attributes including anxiety, anger, impulsivity, and related features.

These personality traits exert a significant influence on the subjective emotional variations observed in students. For instance, individuals with open personalities tend to exhibit more optimism in the face of failures, motivating them to proactively address challenges. Conversely, individuals with neurotic personality traits may display maladaptive behaviours when confronted with similar sources of distress (Ross et al., 2009).

Construction of a Model for Warning Psychological Crises

Building upon the earlier theoretical analysis, it can be contended that emotional responses serve as clear indicators of psychological difficulties, and regular emotional monitoring facilitates the proactive anticipation of psychiatric crises. This study predominantly investigates textual content and visual materials shared by students on social media platforms, denoted as "social media big data" within this research.

Directly observing emotions, especially when applying categorization within the realm of computer science, may at times lack precision. Personality traits and stressful circumstances are perceived to emanate from a combination of internal and external factors, contributing to fluctuations in emotional states. The principal objective of this study is to predict emotions by concurrently examining stressful situations and personality factors. The overarching goal is to formulate a psychological crisis warning model utilizing social media big data.

The evaluation of emotional performance involves assessing the intensity and thresholds of emotions in various categories. Additionally, tracking emotional changes over time is essential for gauging the likelihood that students may experience a psychological crisis. Heightened emotional intensity leading to abrupt emotional changes or prolonged negative emotions serves as an indicative factor for susceptibility to a mental crisis in the student (Watson & Clark, 1984).

The Process of Modelling Preparation

The examination of the dataset on online campus management among students reveals a pronounced preference for the campus network application within the specified age group, solidifying its status as the primary social media platform. The API associated with this application grants access to a substantial volume of user data from the campus network, recognized for its impartial nature and contemporaneous information. Consequently, the principal data source for this study is derived from the social media platform.

Leveraging the campus network's API streamlines the process of collecting and analysing student data, enabling efficient storage in a dedicated database. This database serves as a crucial asset for the computing infrastructure, facilitating effective data management. A comprehensive total of 500 samples were collected from a single educational institution, affording the opportunity for detailed observation, and tracking of the enrolled students (Zung, 1971).

Fundamental Computational Layer

The fundamental computational layer essentially comprises two discrete categories of calculations:

The computation of stress occurrences constitutes a pivotal focus of this investigation, achieved through the analysis of textual content shared by students on social media platforms. This analysis enables a comprehensive understanding of the stressors articulated by students. The Life Change Units (LCU) scale, developed by (Holmes & Rahe, 1967), serves as a tool for categorizing stress experiences into 43 different categories. A study conducted by Chinese researchers utilized the LCU scale to explore the effects of various life events on the Chinese population. Additionally, the researchers introduced the SCALE of Life Experience Units (LEU), a system that categorizes life experiences into 65 discrete categories and assigns LEU values based on different life phases, including youth, middle age, older age, and old age.

Given that many college students undergo the transitional period of early adulthood, the objective of this study was to identify a broad spectrum of stressors commonly experienced by college students. By analysing the youth group dataset from the LEU scale, a total of 15 stress events were identified. These stress events may arise from diverse situations, such as the loss of a parent or the end of a marriage, being terminated from a job or facing academic failure, dealing with a serious illness in the family, experiencing emotional turmoil in a romantic relationship, achieving notable accomplishments or receiving honours, facing traumatic incidents or serious illnesses, starting a new romantic relationship, dealing with disciplinary actions, feeling frustrated during the school enrolment process, participating in political organizations, discontinuing education, encountering setbacks in academic or employment pursuits, and struggling with learning difficulties..

The current study utilized the dictionary approach to quantify stress events. Psychological research has indicated that students' language and context on social media platforms can serve as reflections of situations that induce stress. Consequently, efforts have been made to construct a comprehensive lexicon encompassing events perceived as stress-inducing by students. Initial application of artificial screening procedures aids in achieving the requisite precision and efficiency for lexicon construction.

This study delved into the correlation between language proficiency and the frequency of stress events. Tencent AI Lab developed a word vector model to identify terms with similar semantic meanings. Manual intervention was judiciously applied to deliberately exclude selected words that did not meet specific criteria. In the calculation process, the identification of a phrase from microblog text in the lexicon signifies the occurrence of the corresponding stress event.

In the third phase of the study, the focus shifted to the calculation of personality traits. Extensive research consistently demonstrates that personality traits play a pivotal role in shaping individuals' behaviours on social media platforms. Consequently, it is possible to investigate the personality traits exhibited by college students through the collection and analysis of data obtained from social media platforms.

Through a comprehensive examination of diverse datasets derived from popular social media platforms used by students, the deep learning approach is employed to infer the personality traits of these individuals. Presently, substantial research exists that evaluates personality traits using the "Big Five" personality model within the specific context of Chinese social media.

This study utilized the Heterogeneous Information Ensemble (HIE) processing paradigm, as described by Wei et al. (2017), to assess personality traits, employing the "Big Five" personality model as the standard measure. Deep learning techniques are applied to extract semantic information from various features, including microblog content, user profile image, facial expression, and interaction style. Subsequently, the stack generalization approach combines the semantic information derived from these features, ultimately leading to the formulation of predictions regarding the individual's personality type (Martin, Watson, & Wan, 2000; Wei et al., 2017).

Integration of Emotional Intelligence into Computer Systems

This study introduces a novel emotional calculation algorithm that builds upon previous research findings by incorporating personality factors and stress scenarios. The fundamental principle of this approach can be succinctly outlined as follows: Initial determination of the emotional intensity values for various emotional states in students at a specific moment is achieved through personality assessment and the analysis of stress-inducing situations. Furthermore, the establishment of threshold values for positive and negative emotions is conducted, taking into consideration the personality traits of the students.

To ascertain the specific emotion displayed by the student, an assessment is undertaken to determine if the emotional intensity of each emotion surpasses its respective threshold. The algorithm in question employs Ekman and Friesen (1971) classification system, which categorizes emotions into six distinct categories: disgust, anger, surprise, fear, happiness, and sadness. Negative emotions encompass a range of affective states, including disgust, animosity, fear, and sorrow, while positive emotions encompass affective states such as surprise and delight (Polanczyk et al., 2015).

The Computation of Emotional Intensity

The level of emotional intensity in individuals is closely connected to their decision-making tendencies. By combining personality assessment results with stress event evaluation, it is possible to determine emotional intensity values for six different emotional types displayed by students at a particular moment. The emotional intensity spectrum spans from -1 to 1, with positive sentiments ranging from 0 to 1 and negative emotions falling between -1 and 0.

The Determination of the Emotional Threshold

According to Izard's (1977) study, individuals possess a certain level of emotional activation, and when the intensity of their emotions surpasses this threshold, they may begin outwardly expressing their emotions. In previous studies, researchers have typically treated the emotional threshold as a consistent value throughout the computational process. However, this study introduces a novel approach to determine threshold values for the expression of positive and negative emotions, considering the personality traits of students.

The primary objective of this study is to evaluate whether students will exhibit a specific emotion by assessing whether the intensity of their emotions exceeds the predetermined threshold values. Therefore, a critical aspect of understanding how emotions is expressed in students involves assessing the extent of various emotional categories.

Crisis Warning Layer

This study investigated the probability of encountering a psychological crisis by analysing changes in emotions over time through continuous monitoring. The focus was on observing two distinct phenomena: the rapid oscillation of emotions, transitioning from positive to negative or vice versa within a brief timeframe, and the prolonged persistence of negative feelings. The study introduces a dual monitoring strategy that considers warning value and duration as variables to assess the level of crisis vulnerability among students.

In a recent study by Gupta et al. (2022), various aspects of mood fluctuations were examined using a continuous-time sequence. This included analysing the duration of specific mood states, such as "anger," and studying the temporal transition in emotional intensity, such as the shift from a negative to a positive mood with heightened emotions. Alert thresholds were calculated based on these criteria during specific time intervals. A graphical representation was created to illustrate a system with five early warning signals, whereas the value approaches 1, the level of risk increases.

The engagement of college students in microblogging activities directly influences how they perceive and experience changes in their emotional states and the duration of negative feelings. In the scope of this study, the time series interval is defined as daily units. When learners make more than two posts in a day, the post with the highest emotional value is considered the positive emotional value, while the post with the lowest emotional value is regarded as the negative emotional value for that day (Lyke, 2009).

Material and Methodology

This study employed a hybrid methodology that integrated principles from psychology with machine learning algorithms. The aim was to overcome limitations associated with relying solely on machine learning. This approach facilitated modelling analysis while effectively addressing potential challenges related to probabilistic uncertainties. Drawing upon an in-depth analysis of previous scholarly research and established theories in emotional psychology, this study aims to enhance the existing algorithm for emotion forecasting and introduce a novel methodology for predicting the emotional threshold. Matrix $E = [e_{dis}, e_{ang}, e_{sur}, e_{fea}, e_{joy}, e_{sad}]$ is employed for denoting the emotion type, wherein the components correspondingly represent six emotions: happiness,sadness, anger, disgust, fear, andsurprise.$L = [l_1, l_2, \cdots, l_k]$" emotions based on stress events, respectively.

Table 1

Five Levels of Warning Signal System.

Early warning value	Level	Color
[0,0.2]	Security	Green
(0.2,0.4)	Safer	Blue
[0.4,0.6]	Criticality	Yellow
(0.6,0.8)	More dangerous	Orange
[0.8,1]	Dangerous	Red

The matrix P, represented by the values [po, pc, pa, pn], provides a theoretical framework for categorising different personality types. The classifications align with the spatial arrangement of individuals who display traits linked to openness, conscientiousness, extraversion, agreeableness, and neuroticism, respectively. As an illustration, individuals who possess a personality trait vector P = [0.8, 0.2, 0.7, 0.5, 0] have a tendency towards openness. They demonstrate a preference for tackling challenges with an optimistic mindset. This inclination improves their ability to efficiently overcome challenges. This collection has been identified as the statement discusses the emotional intensity experienced at a particular moment, referred to as "t." It focuses on the emotional intensities associated with the sentiments of disgust, anger, surprise, fear, joy, and sadness at a specific time referred to as "T". The emotional threshold matrix ▲ illustrates the thresholds for emotions, where ωpos signifies the threshold for positive emotions and ωneg signifies the threshold for negative emotions.

The symbol T is used to represent the attenuation function, which controls the modulation of emotions. The symbol Θ is used to represent the influence function of stress events. The symbol Φ is commonly employed to denote the influence function of personality. F represents the computational mechanism that governs the process of emotions, while g serves as a mathematical representation of the warning mechanism. Consider the intensity value of an emotion at a given time, denoted as Iei,t. Additionally, we have the attenuation function Φ, which is associated with the emotion intensity value. The previous level of emotional intensity at time t-1, denoted as Iei,t-1, and the function that describes the influence of stress events on emotions. The stimulus L, which is associated with a stress event that people experienced at a specific time t, and the function exhibit a strong correlation. The personality influence function, denoted as Φ(), is a mathematical concept created to encompass the impact of individual personality traits on the intensity of emotional experiences. The stability of an individual's personality determines the constancy of the personality's influence function. Therefore, this study suggests that the influence of personality on emotional intensity can be understood as a coherent collection of vector values during a defined period.

The function f calculates the activation of a specific emotion based on the emotion intensity (Iei,t) and the emotion threshold at time t. The function g(Ei, t) is used to evaluate the level of psychological distress in students by considering the calculated emotional intensity and values over a specific period of time.

Emotion Attenuation Function

Based on the third rule of emotional intensity, known as the Attenuation Law of Emotional Intensity, the decrease in emotional intensity follows a pattern like an exponential function y = e−λ. Over time, emotional intensity diminishes. In the given temporal context, the emotional intensity is influenced by the preceding time point, referred to as t-1. This relationship is assigned the attenuation factor, λ. A greater λ value results in a more pronounced decline in emotional intensity. Hence, the mathematical representation of the emotional decay function can be stated as T(Ien,t) = Ien,t−1e−λ, where "n" represents a spectrum of emotions, including anger, disgust, joy, sadness, surprise, and fear.

Influence function of stress events

A stress event is a key factor that can lead to changes in emotions. Therefore, the impact of a stress event on an emotion can be represented as Θ(Lk,Iefea,t) = [Lk, Idis,t, Lk, Ieng,t, Lk, Iesur,t, Lk,Iefea,t, Lk, Iejop,t, Lk, Iexad,t]. Lk,Iefea,there denotes the severity of the stress event's impact.

An individual's personality remains consistent and has a discernible and lasting impact on emotion over a specific period. Previous studies have shown that determining the impact of personality on emotion is a complex task. Researchers in the field of psychology have proposed multiple theories to explain the relationship between personality and emotion. Kshirsagar, Molet, and Magnenat-Thalmann (2001) proposed a framework called the "character-motion-emotion-expression" model. In Gebhard (2005) introduced a modified version of this model known as the "character-motion-emotion" model. This study presents a new paradigm that uses the PAD three-dimensional mood space as a mechanism to connect personality traits and mood states. The quantification of mood space is based on three core dimensions: Dominance, Pleasure, and Arousal, which were initially proposed by Mehrabian and Stefl (1995).

Chinese researchers have also studied this characteristic, employing algorithms from previous studies in their analysis (Malekshah, Malekshah, & Malekshah, 2021). In order to examine the relationship between personality and mood, we will introduce two key elements: the mapping matrix K and the mood space matrix M. The transmission of individual moods is mathematically represented by the equation M = P KT. Gebhard (2005) has examined the variable K in detail. To examine the relationship between mood and emotion, we present two important matrices: the transfer matrix F, which represents the connection between motion and emotion, and the emotion space matrix O, which encompasses a 24-dimensional range of emotions. The equation that represents the transmission of motion-emotion is expressed as O = M F, with F being based on the treatment methodology employed in Gebhard's study.

According to Ekman's theory, the 24 dimensions of primary emotions correlate with the 6 dimensions of basic emotions. The computation methodology is outlined in the following manner:

Ip,dis= ODisgust
Ip,ang= (OAnger + OReproach + OHate) × 1/3)
Ip,sur= OSurprise
Ip,fea= (OFear + OFearsConfirmed) × 1/2
Ip,joy= OHappyFor + OGloating + OJoy + OPride + OAdmiration
+ OLiking + OLove + OHope + OSatisfaction + ORelief
+ OGratification + ORelief + OGratification + OGratitude) × 1/12
Ip,sad= (OResentment + OPity + ODistress + OShame
+ ORemorse) × 1/5

Hence, the operationalization of the impact of personality on emotion can be articulated as follows: $\Phi(P)$ = [*Ip,dis, Ip,ang, Ip,sur, Ip,fea, Ip,joy, Ip,sad*]

Emotion Intensity Function

The function representing the emotional intensity at time t can be formulated as:

$I_{en,t} = T(I_{en,t-1}) + \Theta(L) + \Phi(P)$

In layman's terms, the decrease in emotional intensity from the previous moment (t-1), the impact of stress events on emotions, and the influence of personality factors on emotional fluctuations all contribute to the emotional intensity at a given moment (time t).

Threshold Estimation Function

Currently, a common method in research is to establish the emotional threshold as a fixed value, whereas other scholars propose a linear connection between the emotional threshold and personality. It is evident that people exhibit varied reactions when faced with the same stress-inducing circumstances in real life. Therefore, the use of a singular pre-established value or a linear correlation to determine emotional thresholds has significant limitations. A novel approach has been developed to estimate emotional thresholds based on valuable research conducted by Watson and Clark. Watson and Clark's investigation revealed that personality traits, specifically conscientiousness (C) and extraversion (E), have a substantial impact on happiness levels. Moreover, the personality trait of neuroticism (N) significantly influences the occurrence and manifestation of negative emotions. Based on Izard's theoretical framework, individuals who have a lower emotional threshold tend to be more inclined to easily express a particular emotion. For example, if someone is highly sensitive to grief, even a small incident can often trigger intense feelings of sadness.

This study argues that the threshold is only linked to individuals who have conscientious, extroverted, and neurotic personality traits. ξ is a measure of the difference between the positive personality traits (C, E) and the negative personality trait (N), which can be calculated as $\xi = pc + pe - pn$. Furthermore, let ω represent the emotional threshold, which has a strong correlation with ξ. A higher ξ score signifies that an individual's positive personality traits outweigh their negative ones, leading to a greater threshold for experiencing unpleasant emotions. There is a reciprocal relationship between the threshold for positive emotions and the expression of emotions. This suggests that individuals with lower thresholds tend to display positive emotions more readily but may struggle to express negative emotions. In their proposal, Kingdom and Prins (2016) put forward the idea that the psychophysical field developed a comprehensive transition function through a series of carefully conducted experiments. This function aims to explore the connection between the size of a physical stimulus and the corresponding subjective internal response. The rate of internal feeling ascent gradually decreases as the stimulus difference increases.

According to the theoretical framework discussed earlier, this research suggests that there is a similar relationship between the emotional threshold and ξ. The association is expressed using the function ▲, with ωneg representing the negative emotional threshold and ωpos representing the positive emotional threshold. Given the unfavourable nature of ξ when it comes to personality differences, we suggest using the arctan() function to describe it.Incorporating π and dividing by π in the function helps to normalise the estimation within the specified range of [0, 1]. The provided illustration depicts a simulation of the operational functionality of the estimation technique. It is evident that as the ξ value increases, so does the threshold for negative emotions. It can be inferred that the onset of negative emotions becomes more difficult, and their intensity gradually diminishes over time.

Methods

The present study utilised a quasi-experimental design, including a control group, to evaluate the effects of an intervention on a group of young children. District number four was selected using a random technique, which involved three sub-districts. As a result, two high schools within this district were chosen at random to represent the intervention and control groups. These schools have similar educational and environmental characteristics. A total of 210 students participated in the study, with 100 students assigned to the intervention group and another 100 to the control group. A total of 200 participants successfully completed their participation in the study, representing the entire sample. The study analysed different factors related to education and the environment, such as the socio-economic status of the chosen school sites, the subjects and grade levels available, the condition and facilities of the school infrastructure (including recreational and athletic facilities, age of the buildings, presence of green spaces, etc.), student-to-teacher ratios, and the staffing levels at the schools. After taking these factors into account, we proceeded to select participants based on specific criteria: regular attendance at educational institutions, no previous involvement in mental health interventions in the past three years, no substance uses or abuse, and the capacity and willingness to participate independently in the study. The programme ran for a duration of two months. Evaluations of the intervention and control groups were carried out at specific time intervals during the study: before the intervention began and two months after it was implemented.

The study progressed through three distinct phases. During the first phase, students in the intervention group received training in stress management skills. In the following phase, there were changes in the academic environment due to the analysis of test data findings. During the third stage, a programme intervention was implemented with a focus on creating a positive and engaging experience. In contrast, participants in the control group only received standard mental health assessments conducted by the health centre located within the educational institution. The research objective was effectively conveyed to all participants, as well as to at least one of their parents. Participants were given reassurance about the confidentiality of their data. In addition, they carefully filled out and signed a document called the informed consent form.

Measures

Background information was gathered by distributing a questionnaire that covered various demographic variables, including age, family size, and the educational and occupational accomplishments of the parents. The study utilised Persian translations of multiple psychological assessment instruments to evaluate different aspects of well-being. The study employed a range of widely recognised psychological measures, such as the General Health Questionnaire (GHQ-28), the Oxford Happiness Questionnaire, Sherer's General Self-Efficacy Scale, Cohen's Perceived Stress Scale, Snyder's Hopefulness Scale, and Diener's Satisfaction with Life Scale (SWLS). An extensive assessment was conducted to determine the reliability of these measures, utilising Cronbach's alpha coefficient. The resulting values were 0.92, 0.85, 0.81, 0.69, 0.53, and 0.80, respectively. Prior research has provided a comprehensive analysis of the scales, including their scoring, validity, and reliability, within the framework of this population. The Mental Health Promotion Programme is a comprehensive initiative designed to improve mental well-being and reduce the occurrence of mental health disorders.

Designed

The instructional programme followed the McNamara paradigm and lasted for six consecutive weekly sessions. A licensed clinical psychologist led the sessions, which also featured interactive question and answer periods and didactic lectures. After each training session, participants were provided with important training materials in the form of informative booklets. Each session lasted between 45 and 60 minutes.

The Natural Environment

The modifications implemented in the educational setting were a direct response to the shortcomings and unfulfilled requirements highlighted by participants in the pre-test data. The modifications included improving bulletin displays, adding musical interludes during break periods, offering counselling services, promoting a strong relationship between staff and students, and arranging competitive events centred around sports, sketching, and cooking. The intervention programme sought to improve the overall well-being of participants by addressing the identified deficiencies and unmet needs identified in the pre-test data. The topic encompassed a range of aspects, such as physical activity, nutritious eating habits, socialising across genders, methods for fostering personal well-being, and coping with stress.

Statistical data

The data were analysed using numerical values, frequency, measures of central tendency (means), and measures of dispersion (standard deviation, SD). The sign test and McNemar's test were used to compare the intervention and control groups separately. Group comparisons were made by creating cross-tabulations for each mental health predictor in the analysis. The responses were divided into three categories (low, medium, and high) for each predictor individually. A paired t-test was used to evaluate the changes in mean scores of psychological well-being and its related components before and after the intervention. The statistical analyses were conducted using the software programme SPSS v. 17(SPSS Inc. IL, Chicago, USA).

Results

A cohort of 200 participants has successfully concluded their involvement in the research study. The intervention and control groups showed no significant differences in any of the socio-demographic parameters, as demonstrated in Table 2 and Figure 1.

Table 2

Basic Profile of The Participants.

	Study group		Control Group		P value
	Number	Percentage	Number	Percentage	
Gender					0.25
Male	59	59	52	52	
Female	41	41	48	48	
Age					0.15
below 10	7	7	5	5	
10-12	16	16	15	15	
12-15	49	49	54	54	
Above 15	28	28	26	26	
Employment					0.17
Present	12	12	10	10	
Absent	88	88	90	90	
Social economic status					0.38
High	22	22	14	14	
Average	61	61	64	64	
Low	17	17	22	22	

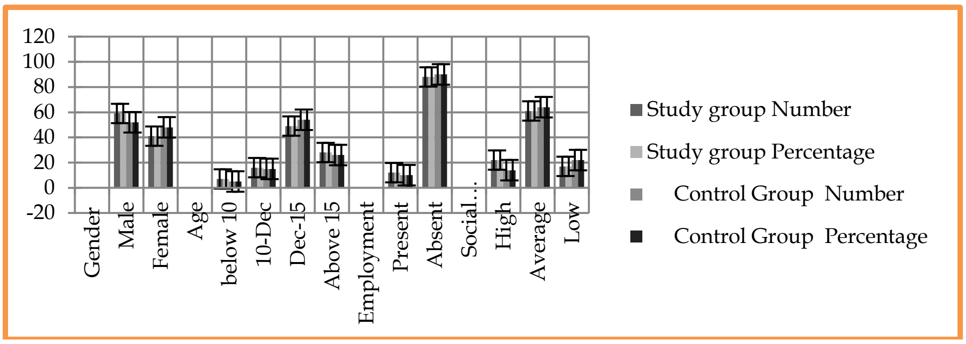

Figure 1. *Basic Profile of The Participants.*

No significant differences in mental health indices between the groups were found at the start of the study, as shown in Table 3 and Figure 2. After conducting a thorough analysis of the intervention and control groups, the findings indicate that there was no notable change in mental health indicators, except for a potentially meaningful connection with a moderate level of happiness (odds ratio [OR] 1.55, 95% confidence interval [CI] 0.89–2.59, p = 0.07). Through the utilisation of a sign test and the examination of pre-post testing data, a noteworthy change in the distribution of GroupWise outcomes was observed between the intervention and control groups. This change was particularly evident in the areas of life satisfaction (p < 0.001) and happiness (p < 0.001).

Table 3

Comparison of Major Variables in Study and Control Groups.

	Study group		Control Group		P value
	Mean	**Sd**	**Mean**	**Sd**	
Self-efficacy	61.58	5.85	59.74	4.98	0.26
Hopefulness	32.15	4.36	31.78	4.11	0.11
Life satisfaction	21.58	3.31	21.74	3.11	0.34
Stress	22.09	3.74	22.55	3.19	0.21
Happiness	1.22	0.15	1.25	0.16	0.14
Psychological well-	32.29	3.14	31.22	3.11	0.15

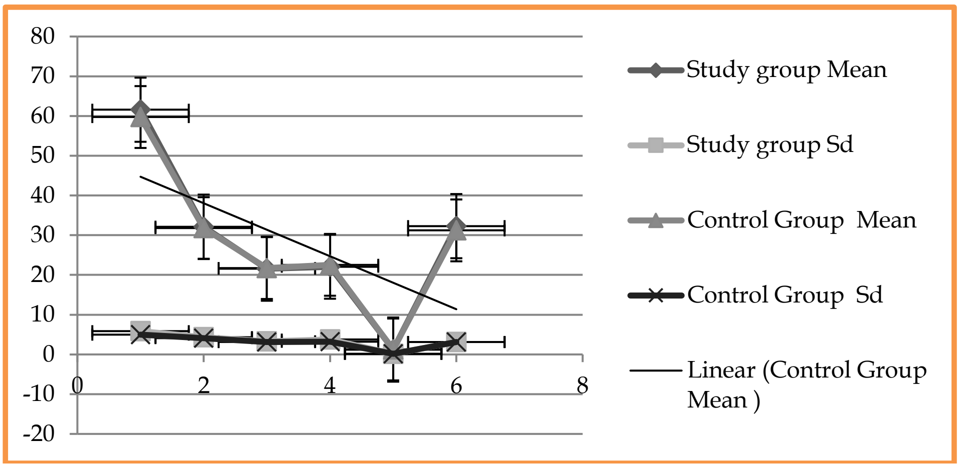

Figure 2. *Comparison of Major Variables in Study and Control Groups.*

According to the information provided in Table 3 and Figure 2, the percentage of participants in the intervention group who reported low levels of happiness decreased from 32% to 25%, while those who reported average levels of happiness decreased from 40% to 30%. It is worth mentioning that there was a substantial rise in the proportion of students in the intervention group who reported experiencing elevated levels of happiness, increasing from 28% to 46%. Table 4 and Figure 3 demonstrate a notable difference in levels of life satisfaction. In addition, there were notable differences in the proportion of participants who reported low and high levels of psychological well-being when considering this aspect.

Table 4

Major Outcome Variables Before and After Intervention in Two Groups.

	Before intervention	After intervention			P value
		Low	Average	High	
Life satisfaction					
Study group					0.01
Low	37	8	10	19	
Average	34	6	9	19	
High	29	10	11	8	
Total	100	24	30	46	
Control group					0.07
Low	34	7	8	19	
Average	29	6	7	16	
High	37	14	10	13	
Total	100	27	25	48	
Happiness					
Study group					0.02
Low	32	9	10	13	
Average	40	8	11	21	
High	28	6	7	15	
Total	100	23	28	49	
Control group					0.06
Low	43	13	8	22	
Average	30	8	6	16	
High	27	7	8	12	
Total	100	30	22	48	
Self-efficacy					
Study group					0.01
Low	31	5	7	19	
Average	41	12	14	15	
High	28	5	7	16	
Total	100	22	28	50	
Control group					0.08
Low	40	14	12	14	
Average	30	12	9	9	
High	30	12	9	9	
Total	100	38	30	32	
Hopefulness					
Study group					0.02
Low	35	15	7	13	
Average	32	13	6	13	
High	33	13	7	13	
Total	100	41	20	39	
Control group					0.07
Low	36	17	13	6	
Average	34	15	12	7	

High	30	13	10	7	
Total	100	45	35	20	
Stress					
Study group					0.02
Low	45	24	7	14	
Average	25	16	3	6	
High	30	20	5	5	
Total	100	60	15	25	
Control group					0.06
Low	42	20	10	12	
Average	23	14	5	4	
High	35	19	10	6	
Total	100	53	25	22	
Psychological well-					
Study group					0.01
Low	35	10	0	25	
Average	00	0	0	0	
High	65	15	0	50	
Total	100	25	00	75	
Control group					0.06
Low	33	13	0	20	
Average	00	0	0	0	
High	67	29	0	38	
Total	100	42	00	58	

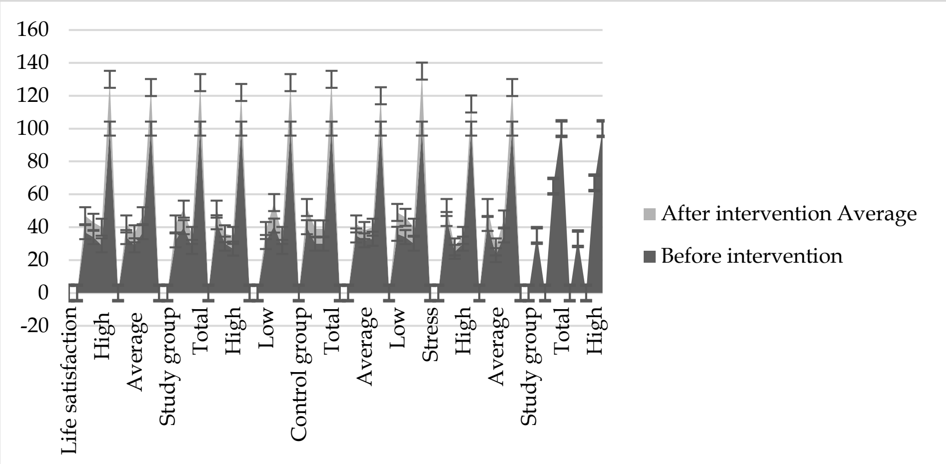

Figure 3. *Major Outcome Variables Before and After Intervention in Two Groups.*

Table 5 displays a comparison of average scores for variables prior to and following the implementation of the intervention. Following the intervention, notable improvements were observed in life satisfaction, happiness, and stress levels among both the intervention and control groups. Significant differences were observed between the intervention group ($p < 0.001$) and the control group ($p = 0.05$).

Table 5

Mean Score Comparison of The Psychological Wellbeing and Its Associated Factors Before and After The Intervention.

	Before intervention		After intervention		p.-value
	Mean	Sd	Mean	Sd	
Self-efficacy					
Study	61.58	5.85	61.89	5.69	0.67
Control	59.74	4.98	62.19	4.99	0.18
Hopefulness					
Study	32.15	4.36	32.65	4.16	0.51
Control	31.78	4.11	33.05	4.66	0.18
Life satisfaction					
Study	21.58	3.31	22.94	2.66	0.001
Control	21.74	3.11	22.77	2.18	0.01
Happiness					
Study	1.22	0.15	1.44	0.19	0.001
Control	1.25	0.16	1.38	0.17	0.04
Stress					
Study	22.09	3.74	20.48	2.63	0.001
Control	22.55	3.19	20.58	2.85	0.01
Psychological well being					
Study	32.29	3.14	30.11	3.11	0.15
Control	31.22	3.11	29.25	3.14	0.11

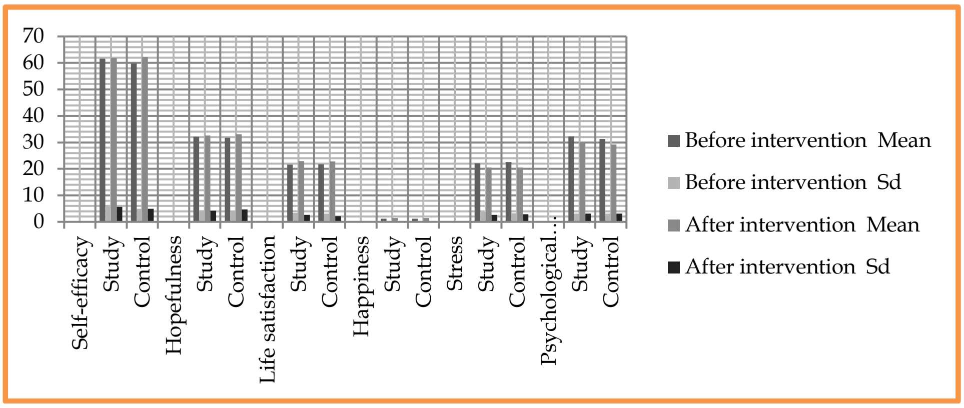

Figure 4. *Mean Score Comparison of The Psychological Wellbeing and Its Associated Factors Before and After the Intervention.*

Discussion

The perception of mental health in our nation has undergone a significant shift, with governments now placing increased emphasis on the well-being of adolescents, youth, and university students. Recent research on a representative sample of 13,486 Iranian adolescents has highlighted the psychological challenges faced by middle school students. The impact on children's mental well-being was attributed to the implementation of a comprehensive intervention in the school setting, encompassing multiple components addressing both physical and mental health. Notably, there was a 33.0% increase in the proportion of students expressing a moderate level of satisfaction. Happiness levels among the intervention group exhibited a significant rise compared to other groups, including the control group (Benyamini, Leventhal, & Leventhal, 2004; Dear, Henderson, & Korten, 2002).

The concept of happiness plays a dual role in the context of optimal well-being, serving as an indicator for assessing societal progress and exerting significant influence on individuals and their social environment. This renders it a noteworthy concept to consider. The results of our study align with previous research, suggesting that increasing happiness can positively impact individuals' mental well-being and overall functioning.

One potential approach to enhancing feelings of pleasure involves promoting increased social interactions and encouraging greater physical activity. Activities such as cooking and listening to music, integral parts of our intervention strategy, have been shown to positively affect happiness levels. Within our intervention, stress management techniques have been observed to independently foster feelings of pleasure. Statistical analysis, however, revealed no significant difference in the happiness parameter between the intervention and control groups within the studied population. This result is not unexpected, considering that stress levels in adolescents can be influenced by various factors, and they often face a diverse array of stressors. These stressors can have a lasting impact on an individual's social, emotional, and cognitive well-being, subsequently influencing overall happiness.

Moreover, our study noted a significant enhancement in the life satisfaction of the participants (Dear et al., 2002; Wilkinson, 2007). The significance of adolescent well-being, particularly in relation to life satisfaction, lies in its direct impact on academic performance and subsequent achievements in adulthood. Mental well-being's role as a critical factor in overall health is widely acknowledged, applicable to both individuals in good health and those dealing with acute or chronic disorders. A low level of life satisfaction is commonly perceived as an indicator of potential hazards or risks. A prior study conducted in the Iranian context found a negative correlation between levels of life satisfaction and educational achievement.

The provided data exhibit similarities to our own findings and align with observations documented in a separate study. The data suggest that engaging in physical and/or mental activities can result in enduring improvements in life satisfaction, emphasizing the significance of internal factors over external ones. Furthermore, our study conducted a comprehensive evaluation of life satisfaction using the SWLS scale, distinguishing it from a previous investigation that employed a single-item measure. Additionally, our study identified changes in psychological well-being that support findings on subjective well-being.

Ongoing scientific discourse surrounds the understanding of psychological well-being and subjective well-being, debating whether they represent separate but related components or a singular entity. Despite alternative conceptualizations, our study opted for Ryff's framework for psychological well-being. Over time, research has revealed that individuals with high levels of psychological well-being exhibit certain biological indicators associated with good physical health, reduced risk, and longer life expectancy. Optimal well-being plays a pivotal role in guarding against the development of mental illness and psychopathological conditions. Previous studies have underscored the long-term consistency of psychological well-being. However, our study's results demonstrate a significant improvement in our sample, consistent with analogous findings in another academic research.

Considering the provided numerical reference, it is worthwhile to contemplate the potential impact on the mental and physical health of the examined adolescents, given the observed enhancement in psychological well-being in our study. The participants' reports of flaws and unmet needs guided the selection of interventions, aligning with similar research suggesting that a personalized approach involving direct interpersonal engagement tends to yield more positive results compared to self-guided interventions or group therapy. Furthermore, recognizing the observed increase in mental well-being, it is reasonable to consider that this improvement may be temporary rather than long-lasting. This phenomenon is often attributed to the challenge of altering a characteristic, especially when there is a time constraint. It is important to note that the participants in our study were deliberately chosen from high schools, which may restrict the applicability of our findings to all adolescents in Iran. It is important to take this constraint into account when evaluating the external validity of our findings. In addition, the notion of happiness can be seen as complex and extremely subjective. Thorough deliberation is necessary when evaluating the measurability and comparability of happiness. Our study has limitations regarding certain factors, such as the familial environment, which has been found to have an impact on mental health.

Following the implementation of the intervention, both the intervention and control groups exhibited significant improvements in life satisfaction, happiness, and stress levels. Prior research indicates that the pre-test environment might influence these results, suggesting the importance of employing more robust experimental designs, such as the Solomon Four-Group Design, in future research endeavours to effectively address potential sources of internal validity concerns. Due to time constraints, the research team conducted a brief follow-up investigation, emphasizing that comprehensive post-project evaluations would offer valuable insights into the initiative's long-term effects.

As is customary, our findings rely on self-reported data from participants. It is essential to acknowledge that social desirability may occasionally influence self-reported measures of well-being. Establishing reliability and validity for objective assessment approaches, such as biological markers or automated behavioural analysis, is crucial for future research.

Conclusion

Our analysis suggests that implementing school-based initiatives aimed at promoting mental health in adolescent females can yield positive effects. These initiatives encompass educational and environmental changes, along with psychophysical strategies that enhance specific aspects of mental well-being, including happiness, life satisfaction, and psychological well-being. The implementation of the SMHPP demonstrates potential for promoting mental well-being among young individuals due to its cost-effectiveness, emphasis on individual needs, and comprehensive approach.

Health authorities should endorse and advocate for effective programs, particularly in poor countries where resources for mental health interventions in schools are often limited. Furthermore, our study underscores the importance of continuous support throughout the program's implementation. Given the challenges of sustaining interventions in educational settings over an extended period, it is advisable for school health policymakers to concentrate efforts on schoolteachers, with a specific focus on school healthcare providers and nurses. These individuals can provide ongoing mental health support to students in a school setting.

References

Benyamini, Y., Leventhal, H., & Leventhal, E. A. (2004). Self-rated oral health as an independent predictor of self-rated general health, self-esteem and life satisfaction. *Social Science & Medicine, 59*(5), 1109-1116. https://doi.org/10.1016/j.socscimed.2003.12.021

Cull, J. G., & Gill, W. S. (1982). *Suicide Probability Scale (SPS) manual*. Los Angeles, CA: Western Psychological Services. https://doi.org/10.1037/t01198-000

Dear, K., Henderson, S., & Korten, A. (2002). Well-being in Australia. *Social Psychiatry and Psychiatric Epidemiology, 37*(11), 503-509. https://doi.org/10.1007/s00127-002-0590-3

Ekman, P., & Friesen, W. V. (1971). Constants Across Cultures in the Face and Emotion. *Journal of Personality and Social Psychology, 17*(2), 124-129. https://doi.org/10.1037/h0030377

Folkman, S. (1984). Personal Control and Stress and Coping Processes: A Theoretical Analysis. *Journal of Personality and Social Psychology, 46*(4), 839-852. https://doi.org/10.1037/0022-3514.46.4.839

Folkman, S., & Lazarus, R. S. (1980). An Analysis of Coping in a Middle-aged Community Sample. *Journal of Health and Social Behavior, 21*(3), 219-239. https://doi.org/10.2307/2136617

Gebhard, P. (2005). ALMA: a layered model of affect. In *Proceedings of the fourth international joint conference on Autonomous agents and multiagent systems* (pp. 29-36). ACM Digital Library. https://doi.org/10.1145/1082473.1082478

Gupta, T., Haase, C. M., Strauss, G. P., Cohen, A. S., Ricard, J. R., & Mittal, V. A. (2022). Alterations in facial expressions of emotion: Determining the promise of ultrathin slicing approaches and comparing human and automated coding methods in psychosis risk. *Emotion, 22*(4), 714-724. https://doi.org/10.1037/emo0000819

Hamilton, M. (1959). The assessment of anxiety states by rating. *British Journal of Medical Psychology, 32*, 50-55. https://doi.org/10.1111/j.2044-8341.1959.tb00467.x

Holmes, T. H., & Rahe, R. H. (1967). The Social Readjustment Rating Scale. *Journal of Psychosomatic Research, 11*(2), 213-218. https://doi.org/10.1016/0022-3999(67)90010-4

Horowitz, M., Sonneborn, D., Sugahara, C., & Maercker, A. (1996). Self-regard: A New Measure. *The American Journal of Psychiatry, 153*(3), 382-385. https://doi.org/10.1176/ajp.153.3.382

Iwendi, C., Huescas, C. G. Y., Chakraborty, C., & Mohan, S. (2020). COVID-19 health analysis and prediction using machine learning algorithms for Mexico and Brazil patients. *Journal of Experimental & Theoretical Artificial Intelligence*, 1-21. https://doi.org/10.1080/0952813X.2022.2058097

Izard, C. E. (1977). *Human Emotions*. New York, NY: Plenum Press. https://doi.org/10.1007/978-1-4899-2209-0

Kingdom, F., & Prins, N. (2016). Psychometric Functions. In *Psychophysics (Second Edition): A Practical Introduction* (pp. 55-117). Academic Press. http://dx.doi.org/10.1016/B978-0-12-407156-8.00004-9

Kshirsagar, S., Molet, T., & Magnenat-Thalmann, N. (2001). Principal components of expressive speech animation. In *Proceedings. Computer Graphics International 2001* (pp. 38-44). IEEE. https://doi.org/10.1109/CGI.2001.934656

Lucas, R. E., & Diener, E. (2001). Understanding extraverts' enjoyment of social situations: The importance of pleasantness. *Journal of Personality and Social Psychology, 81*(2), 343-356. https://doi.org/10.1037/0022-3514.81.2.343

Lyke, J. A. (2009). Insight, but not self-reflection, is related to subjective well-being. *Personality and Individual Differences, 46*(1), 66-70. https://doi.org/10.1016/j.paid.2008.09.010

Malekshah, S., Malekshah, Y., & Malekshah, A. (2021). A novel two-stage optimization method for the reliability based security constraints unit commitment in presence of wind units. *Cleaner Engineering and Technology, 4*, 100237. https://doi.org/10.1016/j.clet.2021.100237

Martin, R., Watson, D., & Wan, C. K. (2000). A Three-Factor Model of Trait Anger: Dimensions of Affect, Behavior, and Cognition. *Journal of Personality, 68*(5), 869-897. https://doi.org/10.1111/1467-6494.00119

Mehrabian, A., & Stefl, C. A. (1995). Basic Temperament Components of Loneliness, Shyness, and Conformity. *Social Behavior and Personality: An International Journal, 23*(3), 253-263. https://doi.org/10.2224/sbp.1995.23.3.253

Polanczyk, G. V., Salum, G. A., Sugaya, L. S., Caye, A., & Rohde, L. A. (2015). Annual Research Review: A meta-analysis of the worldwide prevalence of mental disorders in children and adolescents. *Journal of Child Psychology and Psychiatry, 56*(3), 345-365. https://doi.org/10.1111/jcpp.12381

Ross, C., Orr, E. S., Sisic, M., Arseneault, J. M., Simmering, M. G., & Orr, R. R. (2009). Personality and motivations associated with Facebook use. *Computers in Human Behavior, 25*(2), 578-586. https://doi.org/10.1016/j.chb.2008.12.024

Suryana, D., & Latifa, B. (2023). Inner Child Influence on Early Childhood Emotions. Educational Administration: Theory and Practice, 29(3). https://doi.org/10.52152/kuey.v29i3.693

Watson, D., & Clark, L. A. (1984). Negative affectivity: The disposition to experience aversive emotional states. *Psychological Bulletin, 96*(3), 465-490. https://doi.org/10.1037/0033-2909.96.3.465

Wei, H., Zhang, F., Yuan, N. J., Cao, C., Fu, H., Xie, X., Rui, Y., & Ma, W.-Y. (2017). Beyond the words: Predicting user personality from heterogeneous information. In *Proceedings of the tenth ACM international conference on web search and data mining* (pp. 305-314). ACM Digital Library. https://doi.org/10.1145/3018661.3018717

Wilkinson, W. (2007). *In Pursuit of Happiness Research: Is It Reliable? What Does It Imply for Policy?* (Policy Analysis No. 590). Cato Institute. https://www.cato.org/policy-analysis/pursuit-happiness-research-it-reliable-what-does-it-imply-policy#

Zung, W. W. (1971). A rating instrument for anxiety disorders. *Psychosomatics: Journal of Consultation and Liaison Psychiatry, 12*(6), 371-379. https://doi.org/10.1016/S0033-3182(71)71479-0