Chapter

Reinforcing Positive Cognitive States with Machine Learning: An Experimental Modeling for Preventive Healthcare

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Abstract

Societal evolution has resulted in a complex lifestyle where we give most attention to our physical health leaving psychological health less prioritized. Considering the complex relationship between stress and psychological well-being, this study bases itself on the cognitive states experienced by us. The presented research offers insight into how state-of-the-art technologies can be used to support positive cognitive states. It makes use of the brain-computer interface (BCI) that drives the data collection using electroencephalography (EEG). The study leverages data science to devise machine learning (ML) model to predict the corresponding stress levels of an individual. A feedback loop using "Self Quantification" and "Nudging" offer real-time insights about an individual. Such a mechanism can also support the psychological conditioning of an individual where it does not only offer spatial flexibility and cognitive assistance but also results in enhanced self-efficacy. Being part of quantified self-movement, such an experimental approach could showcase personalized indicators to reflect a positive cognitive state. Although ML modeling in such a data-driven approach might experience reduced diagnostic sensitivity and suffer from observer variability, it can complement psychosomatic treatments for preventive healthcare.

Keywords: BCI, EEG, machine learning, well-being, positive cognitive state

1. Introduction

What if, one day, you wear a hat that would read the negative emotions and alters your thoughts by enacting small tweaks so that you could experience joy? It sounds like a script for a sci-fi movie, but it could also be the future of the healthcare industry. Stress, anxiety, and depression are major global issues; however, less importance is being paid due to their psychosomatic nature. Depression is a disease of modernity—major depressive disorder (MDD), stress, attention deficit hyperactivity disorder (ADHD); our lifestyle, industrial revolution 4.0, work-life imbalance, social media, gadgets, and eating disorders are potential reasons behind deteriorating psychological health [1–3]. Psychological health refers to how we behave, feel, and think.

Furthermore, it determines how skillfully we can manage stressors that are part of our lives. Poor psychological well-being will not only affect our personal life but also have a hazardous effect on our work-life as well [4].

Our cognitive state of mind is continuously affected by experiences at the workplace and by the choices, we make in our personal lives. According to the WHO, 280 million people around the world are suffering from depression [5]. Depression is challenging our everyday life in many ways: unproductivity at work, poor relationship management, loss of interest in life, and at its worst, it can even marshal a person to suicide. The common knowledge is that depression and stress are the same things while both concepts are different. Stress—caused by stressors, i.e., negative cognitive state or emotion/feelings—can be beneficial at times [6]. On the other hand, depression is a ramification of chronic stress, which causes mood disorder, existential crises, and disinterest in everyday tasks and makes us feel sad. Due to the evolution of society, stressors have arisen because of a complex lifestyle. In the process of fulfilling our wish list, our psychological health suffers, causing enormous side effects. Our physical health remains important, but psychological health takes a back seat. Psychological health deteriorates because of chronic stress, which is undoubtedly the genesis of depression and negative cognitive states.

Stress is a complex feeling and stressors are convoluted. The traditional way of understating the potentiality of stressors is a change in lifestyle, medication, and/or talk/cognitive behavioral therapy (CBT); such activities require time, money, effort, and accessibility. These therapies can be used to treat depression, but the techniques and tenure of each therapy are different from the another [7]. This raises the question of the long-term efficacy of these therapies. Apart from long-term efficacy, another problem arises that one must have resources and time to get these therapies. Most of them are offered in 1:1 sessions. It should also be considered that in developed countries there are certain protocols developed for the availability of therapists, convenience for taking sessions, and awareness campaigns to eradicate taboos from society about mental health and mental illness, while in developing countries the case is opposite [8, 9]. Nevertheless, these protocols cannot reach the masses.

Apart from talk therapies, medications and meditations are also used to cure depression and stress.

A systematic review of meditation therapy on 1173 patients having acute and subacute depressive symptoms concluded that meditation may have positive effects on the patients while heterogeneity of techniques and trial designs limits the treatment's generalizability [10]. On the other hand, medications/drugs are a short-term solution to ease stress, and it contains major side effects. If the goal is to promote well-being rather than simply treat sickness, mental health providers must apply novel techniques to assessment and therapy [11].

Patients have typically been treated by medical personnel as passive recipients of their treatment in the healthcare industry [12]. It is necessary to reevaluate this passive viewpoint, which has been pervasive in the healthcare industry [13]. Additionally, research based on well-being needs to be integrated and applied so that health practitioners may involve their patients and provide better results. One of the most debated topics in today's healthcare scenario is how to employ technology to improve access to and quality of care, as well as the patient experience [14]. Technologies such as A.I. and Healthcare IoT have been widely deployed in a variety of industries, with healthcare being one of them. As technology can play its role by offering affordable and accessible solutions. It does not limit itself to physical health [15] and can go beyond to serve as a critical element for reinforcing positive cognitive states.

Today, technology is capable to change the dynamics of the traditional way of dealing with depression, anxiety, and stress. Following these advances in technology allows us to study and analyze the brain more accurately than before. One of the breakthroughs is electroencephalography (EEG) was commonly used to detect a tumor, epilepsy, sleep disorder, brain death, and coma. Brain-computer interface (BCI) is a system that connects a human mind to a computer to link the brain/brain activity to a computer. BCI is a noninvasive system that has used brain signals to offer a communication system. Apart from improving the sensorimotor function of humans, BCI also offers therapeutic paradigms. The elements of BCI are the detection of brain activity, categorizing it, give feedback in real-time [16].

BCIs are not limited to the recording paradigms but also consider the "will" of the user who generates signals. The "will" of a user is divided into three categories; 1) the subject is willingly producing a signal for which the spontaneous BCI system would be used, 2) the subject is being exposed to certain stimuli produced by the evoked BCI system and generates a signal and 3) the subject uses normal arousal activity or signal produced by a brain of the subject for which passive BCI system would be used. Building on studies of value co-creation and smart technologies, scientists are considering the opportunities that how smart technologies and tech-enabled healthcare can help practitioners and patients. As proposed in this chapter brain-computer interface can enable patients to track themselves and can be used to read the data provided by the patient. A.I. leverages digitized data to provide smart nudges to prevent behavioral risk factors. Catapulted by the stream of data, the A.I. interacts with people based on their lifestyle and emotional states and permits expression of autonomy for reinforcing positive cognitive states, which increases their self-efficacy for preventive healthcare.

2. Literature review

2.1 Psychosomatic health

We live in volatile times with constant stress, where the source of stress are personal relationships, workplace pressure, and financial problems, together known as "stressors" [6]. We frequently hold onto this stress, allowing its negative effects to build up. Such circumstances may result in serious health issues such as anxiety and depression [17]. When compared to the number of individuals who experience it, research on mental health is inadequate, and this disparity is especially glaring for low- and middle-income nations [18]. Psychosomatic health reflects both mind and body. At any given time, our mental health influences our physical health. Certain physical conditions and diseases are especially vulnerable to being exacerbated by emotional variables like stress and worry. Considering this, it is crucial to pay attention to both physical as well as mental health. The balance of both can result in the well-being of an individual's health. The link between physical and psychological health is significant and the prevalence of mental diseases is rising [19]. It has grown to be a serious public health problem that affects people worldwide.

Mental health professionals must use cutting-edge techniques for assessment and counseling if the intention is to promote well-being rather than only treat illness [11]. Research into mental illness is developing quickly, with help from studies in the fields of genetics, genomics, psychiatry, and epidemiology, among others. Clinical practice should continue to be informed by these advancements at an exponential rate. Patients have typically been treated by medical personnel as passive recipients of their treatment in the healthcare industry [12]. The challenge is also to apply and integrate the body of research on well-being so that health practitioners may involve their patients and achieve better outcomes.

2.2 Constructs of well-being

Well-being is a multifaceted construct that is affected by human sentiments of feeling happy, cheerful, and excited [20]. Research states that psychological well-being has cognitive appraisals [21] and can be operationalized with indicators that represent positively balanced emotion as indicated in **Figure 1**.

Stress levels have a deleterious impact on psychological health [22] and there exists strong evidence to support the relationship between stress and psychological health [23]. Data have also shown a considerable negative correlation between psychological well-being and perceived job stress. Among the psychosocial risk factors frequently examined concerning poor health are anger, anxiety, depression, and social isolation. A positive cognitive state is concerned with positive psychological states (e.g., happiness), and positive psychological traits (e.g., interests). Concern for positive health leads to an examination of health assets, and individual-level factors that represent positive cognitive states [24–26].

2.3 Significance of technology

Replication and the use of technology to enhance the patient experience, access to treatment, and care quality are one of the most contested issues in today's healthcare environment [14]. Technologies such as IoT have been widely applied across industries including healthcare [27]. Its capabilities are expected to expedite medical procedures, provide individuals with more control over their medical information, and improve the general quality of medical results [28].

Early healthcare research was limited to clinicians, psychologists, behavioral scientists, and therapists, but today, mapping of brain activity is possible through computers; initiated with functional magnetic resonance imagining (fMRI), a radiation-less, noninvasive, and accessible technological breakthrough. A recent innovation in brain imagining includes trans-cranial magnetic (TCM) stimulation

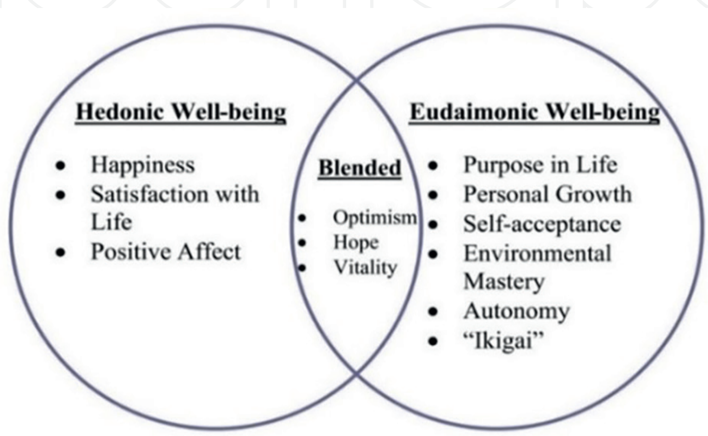

Figure 1.
Conception and categorization of psychological well-being.

a coil placed on the head of the subject that generates a magnetic field and stimulus that allows the subject to perform some activity through the mind without using peripheral nerves and muscles. At the same time, today, EEG-based brain-computer interphase (BCI) is also being used to study brain activity. Initially, the technology was used to allow people—physically disabled—to perform their routine tasks using brain signals connected with BCI that controls robotic limbs. As a matter of course, scientists also worked on the assumption that "if a human can control the machine through its brain, then it is also possible to control the brain through a machine" [29].

BCI can record brain signals in two ways: 1) noninvasive recording of brain signals through the scalp using electroencephalography (EEG), functional magnetic resonance imaging (fMRI), and near-infrared spectroscopy (NIRS); 2) invasive recording using electrocorticography (ECoG) by placing electrodes on the surface of the cortex and microelectrode arrays placing within the cortex or inserted into a single cell.

The above approaches have their merits and demerits. Invasive technologies are associated with more risk due to the requirement of the surgical method, but it gives a higher signal-to-noise ratio. On the contrary, noninvasive technologies are more popular than nonsurgical methods for their cost-efficiency, portability, and safety purposes, however, the quality of the signal-to-noise ratio—the intensity of brain signals to noise intensity—is lower as compared to invasive technology. Thus, exploring the opportunities and challenges of artificial intelligence (AI) in healthcare it can be confirmed that A.I. can be used to perform diagnostics and assisted well-being [30]. It indicates how technology can relinquish ubiquitous connectivity for the betterment of health services [31].

Technology is the driving force behind the healthcare industry, and it dramatically predicts the future. While we might speculate about healthcare trends in the future, we must take proactive measures to guarantee the best results for society [32]. Although implementing cutting-edge medical technology can be expensive, research indicates that the social value of living longer and healthier lives should be prioritized over the expense [33].

A.I. facilitates value creation by enhancing the resource exchange process resulting in expanded interaction capabilities and co-created value for both parties. With the potential for value co-creation, A.I. enables service providers to attain an unprecedented level of reliability [34]. The focus shifts from individual technologies (and devices) to the socio-material practices enabled by the application of the A.I. and IoM in healthcare [35]. A.I. approaches will mature and could help mental health practitioners redefine mental issues more objectively and personalize therapies [36]. More effort is required to bridge the divide between mental health clinical care and AI research. Implementing artificial intelligence in healthcare is a compelling concept that has the potential to lead to major advances in accomplishing real-time and tailored treatment at lower costs [37]. Even though these systems face numerous methodological and ethical issues, they have the potential to permit large-scale data collecting far beyond the scope of typical research laboratory settings [38]. From deep learning to control of health management systems, its informatics-driven techniques and active physician guidance in treatment decisions cannot be ignored [39]. A system is a complex object made up of interdependent parts that interact with one another and with their environments and it exhibits continuous evolution by assimilating new attributes for emergence [40]. Systems theory can be applied in service science to investigate phenomena from a holistic approach [41] where observed reality can be perceived as an integrated and interacting unicum of phenomena [42].

Connections between cognitive technologies and humans can establish intricate service networks with novel value propositions [43].

2.4 Quantified self

Self-tracking, commonly referred to as "quantified self," is increasingly popular in the healthcare industry [44]. Several people are embracing self-quantification where they can receive "self-knowledge via numbers" in the hope of improving their well-being [45]. Self-tracking technology has raised expectations, if not outright hype, for helping people manage their health risks and promote optimal wellness [46]. However, because of the discrepancies between personal experiences and self-tracking data, strong expectations could not always be realized. This is a concern if people are expected to participate more in the collection and analysis of their personal data for their health and well-being. The ability to self-track would translate into the management of patient health and ease the process of making wise therapeutic decisions [47]. One of the main characteristics of self-tracking is how users respond to self-tracking data. The findings show that mentality plays a crucial role in defining the self-tracking experience. Even though self-tracking positively affects customers' impressions of personalization [48], its data-driven and quantifiable features might occasionally result in excessive self-monitoring. This could put more pressure on the user to perform following strict health standards, which could cause feelings of inadequacy and make it difficult for them to enjoy exercising [49]. Meanwhile, several studies have noted an increase in self-efficacy in relation to self-quantification [50, 51].

2.5 Nudge theory

"Nudge theory" proposed that an intervention aimed at modifying the cognitive boundaries may gradually alter the actions of an individual [52]. When nudge seems to be people's declared self-interests, such intervention need not deal with the negativity of traditional enforcement. The behavioral sciences have created nudge to change behavior, which challenges the conventional use of regulation in public health policy to address modifiable individual-level behaviors. Nudging interventions are marked as "a rearrangement of a decision context that softly encourages a specific choice" [53] as well as "physical modifications in the choice architecture that predictably influence people's choices." These interventions change how humans make choices, which contributes to cognitive biases—that is, changing how options are presented to individuals—so that people's cognitive biases drive them to act in their own best interests, the best interests of societies, or both. While decision-making biases can be used to encourage individual health behavior, straightforward interventions can encourage people to make the best possible decisions for their health without affecting the decision-makers' freedom of choice [54].

Further, nudging techniques have been applied for improving user engagement in mental health and reinforcing positive cognitive states using technologies [55]. In the assessment of the self-tracking process, in many use cases, the individual benefits through a sustained engagement in the process and use of self-tracking technologies [56]. According to this study, routine tracking may enhance patients' self-efficacy and help them develop their self-management skills more effectively than event-driven recording. Both self-efficacy and self-management skills are linked to better health outcomes [57].

2.6 Positive cognitive states

Reinforcing positive cognitive states is synonymous with a condition of flourishing that includes health, happiness, and prosperity and includes an individual's emotions as well as their overall assessment of life satisfaction. It is a key result in health research that assists in determining the effectiveness of therapies and treatments as well as understanding patients' experiences [58]. A review of literature by Ref. [59] suggests positive cognitive states through well-being encompass diverse experiences that include positive affective states, low levels of negative affective states as well as good psychosomatic health. The definition of well-being should include a positive psychological state rather than only the absence of mental illness [60]. Individuals' well-being—as healthcare customers' perceptions—is a highly desired outcome of interest to both researchers and practitioners [61]. This study examines positive cognitive states which include a person's feelings like despair and anxiety, from the perspective of preventive healthcare. The latest pandemic's psychological effects necessitate the creation of an intervention to enhance mental health [62, 63]. The positive feelings that are impacted by stressors [64] from the outside world could be used to gauge one's level of well-being [3]. When subjected to stressors, the "stress" underlines the response by the heart that outweighs the individual's perceived ability to cope with it [59, 65]. Despite being a subjective notion, well-being does reflect the effects of stress, and [66] confirmed that a decrease in stress results in improved well-being. As a result, a person's well-being can be determined by how they react to changing pressures and retain positive cognitive states [67]. It should be a top priority to look at the aspect of preventive healthcare and to do this, it is crucial to track each person's degree of stress [68].

2.7 Research gap and objective

Based on the review of the literature, we understand that the gap exists in finding the role and impact of the technology on reinforcing positive cognitive states. Hence the research objective for the given study is to ascertain whether positive emotions contribute to well-being and check how that translates into organizational productivity.

3. Research method

The presented research is based on an exploratory study that is fueled by qualitative data collection and its A.I.-driven analysis. Its "Mixed mode" approach has been well-established for merging complex research designs [69]. In this study, it was important to understand whether psychological health affects physical health. Upon confirmation, it needed to establish whether the involvement of technology can enhance well-being. Finally, the last stage looked at emotional states and energy levels on workplace productivity. Hence the research methodology adopted "Sequential Multiple Methodology" that had been divided into four stages [70]. These stages were utilized to observe the occurrence of a phenomenon to improve psychological well-being. A statistical analysis tool was utilized for the multivariate analysis required to fulfill the research objective.

The machine learning (ML) modeling supported developing illustrations of essential trends and variations presented in the given study. It operated on the data retrieved using electroencephalography (EEG). A device that made it possible is called a brain-computer interface [71]. With five EEG electrodes at the AF3, AF4, T7, Pz, and two reference electrodes, BCI recorded brainwaves and produced precise band activity with defined frequencies. Alpha waves are a representation of the brain's natural "relaxed" and "alert" states. A beta wave is connected to active attention and thinking activities. Drowsiness, arousal, and meditation are all characteristics of theta activity. Gamma rhythms develop when distinct groups of neurons work together to carry out challenging cognitive or physical tasks. It reflected upon the emotional states experienced by the subjects. Considering the complex nature and interactions of brain signals A.I. played a significant role in this stage. As EEG data have thousands of instances recorded in a second; it becomes extremely difficult for health professionals to reflect on the tremendous volume of generated data.

Simultaneously, quantitative data metrics were collected from the subjects in the form of a questionnaire that included both quantitative and qualitative questions. Both BCI data and survey data were used to understand workplace productivity. The construct for depicting "Workplace Productivity" included stress (represented by age, lifestyle, and emotional states) and energy levels (using sleep pattern and circadian rhythm). Given study deployed "stratified sampling" that has put a narrow focus on similar characteristics of the research population that was collected from India in consideration of ethical guidelines. Power analysis for linear regression was completed in G*Power using an alpha of 0.05, a power of 0.80, a large effect size ($p = .5$), and two tails to establish an adequate sample size. Based on the aforementioned assumptions, the ideal sample size is 26 [72].

3.1 Data modeling

The latter part of the study was used for ML modeling using a decision tree as a statistical technique. Considering a large number of data points and to derive real-time insights, the presented research opted for data science-driven techniques using ML-driven modeling [73].

Although such data modeling provides greater depth of the impact of predictors on the dependent variable psychosomatic construct can be complex to evaluate. This is because the brain generates relevant waves multiple times in an instant. It could even go as far as thousands of instances per second. Hence for a particular instance, the value of stress keeps on changing with interest, relaxation, excitement, focus, and engagement as mediators. Thus, evaluating the state of health of an individual as a particular instance calls for a holistic approach in consideration of the signal emitted by other cortices of the human brain. Such calculations could get very complex; hence

Figure 2.
Development of machine learning model.

in the given study, machine learning is used to predict the possible instance based on the historical data and patterns.

As shown in **Figure 2,** the power of prediction granted by data science can make an individual proactive toward their state of health, and the same has been used in the study as a preventive and personalized way to attain positive cognitive states [37].

4. Findings

The "Sequential Multiple Methodology" in this research aligns four stages of the study including the pilot study that draws insights using both qualitative and quantitative techniques. A pilot study shows that mental health has a certain impact on the individual physical health **(Stage I),** confirming the existence of the "Psychosomatic" nature of the health aspect. The variables in play include—Psychological_Issue, Subconscious_Mind, Bio_Signatures, Physical_Issue, Conscious_Mind, Therapeutic_Intervention, Role_of_Technology, Personality_Dimensions, and Psychosomatic_Health. The same can be proven through "Pearson Correlation" that displays a significant positive correlation was observed between Psychological_Issue and Physical_Issue.

The next stage **(Stage II)** cascades the above finding to identify the role of technology on individuals' well-being. Using qualitative illustrations such as "Sentiment Analysis" and "Co-occurrence Table." Both these techniques make sure that case study selection stays balanced and with minimal bias. It identifies eHealth as an emerging trend and supports the application of A.I. for the exploration of cognitive states. The same was confirmed with qualitative comments from the health professionals and relevant case studies were analyzed using qualitative content analysis (QCA). **Stage III** of the research design—being the most critical one—treats Psychological Well-being as a multidimensional construct, and as a product of emotions, happiness, and positive affect. During this stage, the results of the linear regression model were significant, $F(12,1509) = 1584.37$, $p < .001$, $R2 = 0.93$, indicating that approximately 93% of the variance in STRESS is explainable with the Regression Equation. It verifies the fact that sustained stress and negative feelings experienced by a person can potentially affect individuals' well-being.

In this part of the study, a data-driven machine learning model (Refer to **Figure 3**) was used to bridge the information silos and create a personalized model to assist with stress management. It reflects that, with the self-learning technology offering insights in real-time, it would be easier to maintain or improve psychological well-being. Furthermore, this stage also confirms that positive emotions contribute to well-being. In such an exploration, we can gain a greater understanding of how technology contributes to the improvement of well-being.

Workplace productivity is explored in **Stage IV** of the research design, where, as an emotional state, "Focus" plays an important role. It uses Spearman correlation among variables including AGE, BMI, FOCUS, CIRCADIAN_RHYTHM, GENDER, STATE_OF_HEALTH, STRESS, ENERGY_LEVEL, LIFESTYLE, ENGAGEMENT, SLEEP, and OBSERVED_PRODUCTIVITY. A significant negative correlation was observed between FOCUS and OBSERVED_PRODUCTIVITY ($r = -0.12$, $p < .001$, 95% CI = $[-0.17, -0.07]$).

The correlation coefficient between FOCUS and OBSERVED_PRODUCTIVITY was—0.12, indicating a small effect size. This correlation indicates that as FOCUS increases, OBSERVED_PRODUCTIVITY tends to decrease.

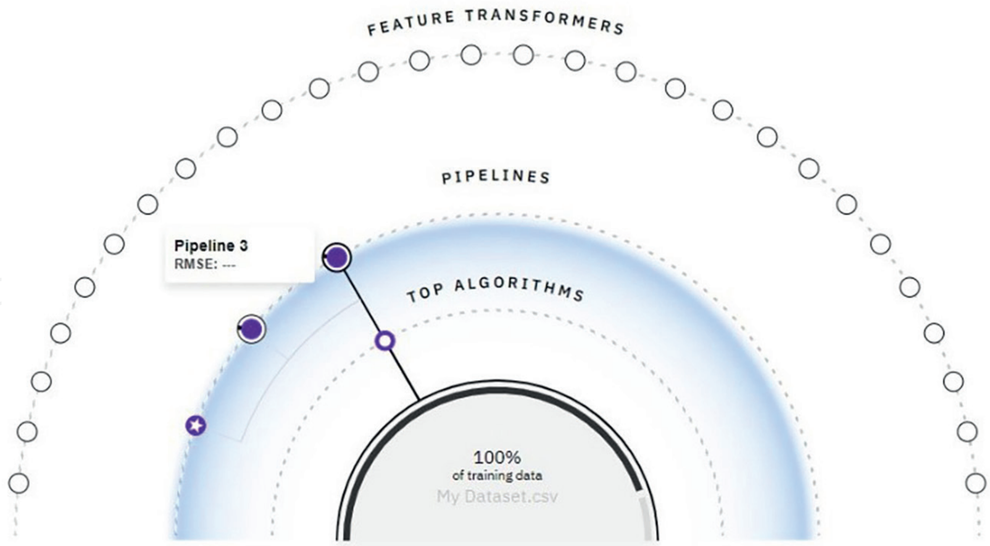

Figure 3.
Feature transformation of ML model.

Using establish constructs the energy levels of a person can be understood using the historical data on circadian rhythm and sleep patterns. Optimal stress and energy levels were used to measure workplace productivity [74]. In this process, stress is moderated by engagement, interest, focus, and relaxation states. Self-quantification (of cognitive indicators) can be augmented using A.I. where nudges dynamically become smart nudges that offer positive cognitive states. Additionally, this stage reviews prior academic literature to reflect on how workplace well-being drives organizational performance. As a result of the literature review conducted for this study, we understand that allows us to reflect on the co-created value for an organization through individual well-being.

Observing the effect of emotional states and psychological well-being.

- From Stage III of the research design, we can observe that stress levels are strongly correlated with the emotional states of individuals.
- There are three variables involved in this process: stress, interest, and relaxation.
- Self-quantification is an effective method for maintaining psychological well-being, which is a product of a person's emotional state.

Observing the impact of psychological well-being and workplace productivity.

- Using Stage IV data, we can determine that an individual's Focus directly impacts their workplace productivity.
- A mediator in this process is "Focus," while moderators include "Body's clock" and "Energy levels."
- Additionally, the current knowledge may be linked to relevant academic literature to conclude that workplace productivity has a direct impact on organizational performance.

5. Discussions

The research addresses the evolution of practices driven by these technologies and how they advance the multiple aspects of healthcare. The capability and scalability of the technological platform are likely to support inclusive and sustainable enhancement in psychosomatic healthcare. In the study different emotional reactions were evoked from the subjects during data collection. EEG frequencies from five different cerebral cortices were included in the data that was gathered: ALPHA, BETA (H), BETA (L), GAMMA, and THETA frequencies. By identifying the significance of each frequency, scaled values were calculated for attributes such as engagement, focus, excitement, interest, relaxation, and stress. Using data science, a machine learning (ML) model was trained to identify the probable effect of "Stress" as a target value for prediction.

The algorithm learned from the data and predicted the target values with higher accuracy, as shown in **Figure 4**. Thus, findings from the study largely shed light on the occurrence of psychosomatic illness and the potential contribution of technology to improving psychological health. Later, through data-driven research, the study analyses emotional states and personal well-being. For the fulfillment of this study, two constructs were used to identify Stress and predict Productivity. The construct of stress relied on the degree of "Interest" and "Relaxation," while the construct of productivity was dependent on the "Focus" and "Engagement" levels of an individual.

5.1 Cognitive attributes

An electroencephalograph (EEG) reflects neural oscillations generated by the human brain. These brainwaves can be read using a brain-computer interface (BCI) and converted into scaled values for analysis. Such a setup can be used to enhance psychosomatic health using a data-driven model. Measures including age, state of health, engagement, relaxation, interest, and focus significantly affect the stress levels of a person, of which, the relaxation and interest levels are the most prominent ones. In the healthcare ecosystem, brainwaves interact with applied therapeutic Interventions and integrate resources to reflect on current lifestyle and state of health.

Measures	Holdout score	Cross validation score
Root mean squared error	0.029	0.027
R squared	0.929	0.939
Explained variance	0.930	0.939
Mean squared error	0.001	0.001
Mean squared log error	0.000	0.000
Mean absolute error	0.019	0.020
Median absolute error	0.014	0.014
Root mean squared log error	0.020	0.020

Figure 4.
Machine learning model performance.

Feature name	Transformation	Feature importance
INTEREST	None	100.00%
RELAXATION	None	45.00%
INTERVENTION DENSITY	None	6.00%
SLEEP	None	5.00%
NewFeature_1	nxor(ENGAGEMENT,RELAXATION)	5.00%
NewFeature_9	nxor(INTEREST,FOCUS)	4.00%
LIFESTYLE	None	4.00%
AGE	None	3.00%
NewFeature_2	nxor(ENGAGEMENT,INTEREST)	3.00%

Figure 5.
Summary of ML model's features importance.

This provides an individual with a relaxed state of mind releasing stress. With such an approach, therapists can diagnose and offer prognosis of stress levels for the betterment of cognitive states. Using artificial intelligence and managing individual attributes, it is possible to achieve optimal stress levels. The emotional and physiological response to unmanageable and unpredictable circumstances is perceived as "Psychological Stress." It is a reflection of the intense stress caused by difficult cognitive tasks completed under time and social constraints. It is established that factors connected to "Individual Lifestyle," "Brainwaves," and "Therapeutic Intervention" affect an individual's stress levels based on the low p-value (.05) of the indicators. Age, gender, and state of health (Prior) are uncontrollable, as data analysis reveals; however, the intervention density can be changed to induce varying levels of stress in a person. The ML model summary report presented in **Figure 5** confirms that psychologists or psychotherapists can modify degrees of focus, interest, relaxation, and engagement at the same time to enhance cognitive state.

5.2 Reinforcing positive cognitive states

According to the aforementioned observations, a person can use an ML-driven model to maintain a predicted level of Interest and Relaxation while achieving an optimal level of Stress. An ML model's insights can greatly aid Therapists in their efforts to comprehend and treat the psychosomatic disease. The connection between interest and relaxation may be used by a therapist to promote beneficial effects. The ML model produced by BCI can be applied in real-time and can shorten the time needed for therapists to treat patients for psychosomatic conditions. The validated model can be enhanced by the patient to improve their health and minimize expenditures associated with it.

The process of enhancing psychosomatic health can be accelerated and optimized using the ML model. In the process, value is created by the interaction of actors in healthcare, where this type of psychotherapy can be accomplished in a short amount of time with the use of the proposed experimental ML model. By scaling the model in the form of an App and Web portals, more people can get access to the healthcare ecosystem. Moreover, the well-being of an individual helps their respective organizations, enabling long-term growth. In line with self-tracking, people could reach a desired mental state (with or without help from therapists).

The approach mentioned in the given study would help people gain greater self-control and stay in the productive zone. This research offers the individual to increase their productivity and, in turn, enhance organizational performance. When combined with traditional statistical hypothesis testing, machine learning holds tremendous promise for the development of new models and can reveal interactions, hidden patterns of abnormal activity, brain anatomy and connections, and brain and physiological behavior systems as well as positive cognitive states.

6. Implications

6.1 Personalized approach

This study will help health practitioners analyze individual health indicators to customize their approach to enhancing psychosomatic health. EEG biofeedback can predict stress and energy level and can generate a signal that indicates a personalized level of engagement and focus of an individual. These signals would be generated by measuring the sleep patterns, stress levels, and circadian rhythms—that further helps individuals. With the help of a BCI device, the ML model would create nudges to forewarn these stress levels and additional mediators of well-being. When an individual would be able to measure the focus and engagement level, it would help him/her create work-life balance. This approach would give an individual an opportunity to rejuvenate their cognitive states of mind and the individual would be able to enhance their workplace productivity.

6.2 Enhanced self-efficacy

The technology in this study is wearable, and it can generate real-time data to improve individuals' well-being and offer personalized nudges. The ability conferred by the application of technology offers greater self-efficacy as the predictive power of ML will provide instant biofeedback. The data generated through ML could not only help individuals but health practitioners to provide "cognitive assistance" [75]. The noninvasive wearable accessories designed at a low cost will help the masses to personalize and reinforce positive cognitive states. Such machines will enhance individuals' self-efficacy and productivity; they will also reduce healthcare costs [76]. Healthcare services will be able to preserve the data generated through these devices and manage it by creating a healthcare ecosystem, and the data will offer portability. This entire process as a whole will reinforce positive cognitive states [52] for preventive healthcare.

6.3 Effective treatment

Brain-computer interface (BCI) will provide real-time data to give masses accessibility and portability to health-related data. Machine learning-driven models will reduce the time required for psychosomatic health treatments. Such models produced using A.I. will help individuals and therapists' access and re-evaluate the data at any time to reduce the cost and time. Thus, the machine learning model would expedite and optimize the process of augmenting cognitive states.

7. Limitations

As a data science-backed study it's not immune from the limitations on its own. Where the enrichment of results is dependent on the data quality and quantity. The accuracy of the data provided by BCI devices depends on the quality of the data captured by the subject. Hindrance in the data by the movement of the subjects during data collection or the unconscious reservations by the subject can provide garbage data to the ML model. Also, data modeling for this specific study utilizes features from the available dataset; hence its accuracy depends on certain boundaries of 5-channel brain-computer interaction [77]. By obtaining neural data from 14- or 32-channel EEG sensors, the same can be improved. Although the study maintained constant efforts to optimize data models, overfitting data in machine learning may lead to less clarity in the outcomes. Additionally, the application of data-driven analytical modeling in healthcare may have decreased diagnostic sensitivity. It may keep certain data that cannot be fitted into ML models out of focus. Such modeling may also appear complicated and multidimensional at the time, with a risk of disappearing and missing out due to observer variability.

In the future however application of ensemble modeling or neural networks, such study can be reinforced for greater reliability of results. Also, in the given study the constructs of well-being only focused on the "positive affect" of Hedonic well-being. While such a construct appears robust; it did not include other dimensions (such as happiness, hope, and self-acceptance) which may be due for consideration in future studies.

8. Conclusion

This book chapter extends the discussion on how digital technologies such as artificial intelligence (A.I.) and the Internet of medical things (IoMT) are changing health-related service provision and experiences. Their combination results in the effective sharing of health data and monitoring of real-time health, presenting personalized treatment options to the patient. The chapter reiterates the importance of technology—such as artificial intelligence as a component of healthcare services where a dynamic configuration of people, technologies, and positive cognitive states and highlights the link between mental and physical health. The study also reflects on how psychological health affects productivity at work. The research design makes extensive use of data science to fulfill its objectives that explore the role of positive emotions for the betterment of well-being using A.I. and reflect upon the co-created value in an organization through reinforced positive cognitive states brain-computer interfaces (BCIs) gather electroencephalography signals from the subjects and use machine learning to predict future cognitive states. The construct is pivoted on the significance of positive emotions, relating to stress, which has the potential to improve psychological well-being. The ML model predicts a person's stress levels as well as their link with "Interest" and "Relaxation." Continuous self-quantification fueled by positive emotions through "Self-tracking" and "Nudging" can improve psychological well-being. Moreover, the study offers significant insights into how positive cognitive states could enhance workplace productivity, ultimately resulting in greater organizational performance. We can infer that ML models can support psychotherapies to minimize time to therapy and increase patient access. In addition to reducing treatment time, reducing costs, and increasing patient access to the healthcare ecosystem, the outcome offers self-efficacy that can be effectively provided by the spatial flexibility and cognitive support generated from the iterative process. When dealing with AI-driven models, however, there are limitations including overfitting of data, diagnostic sensitivity, and observer variability.

9. Notes/thanks/other declarations

This book chapter reflects an experiment carried out during doctoral work and uses proprietary technology to draw presented insights.

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