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MACHINE LEARNING IN THE WORKPLACE AND IN EDUCATION FOR STRESS MANAGEMENT: A SYSTEMATIC LITERATURE REVIEW OF APPLICATIONS

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ABSTRACT

The world of competition puts a note on stress and becomes an integral part of everyone's life and directly or indirectly affects individuals in many ways. The COVID-19 pandemic has had a tremendous impact on the economy, education, health care, the business sector, and other aspects of society in every imaginable way, with stress, anxiety, and depression. It even glorifies the importance and importance of managing stress, anxiety and depression. The purpose of this study is to identify all possible personal, occupational, psychological, and interpersonal reasons that contribute to stress, anxiety, and depression affecting individuals with vibrant professional backgrounds using machine learning. to identify the factors of Our study aims to define and explain the impact of technological advances and the COVID-19 pandemic on individual stress levels. It includes various supervised and unsupervised machine learning algorithms for efficient and effective detection of stress in large populations. The purpose of this study is to sensitize millions of people to early detection and treatment of stress before it becomes life-threatening. The paper concludes by highlighting how stress-related research can help policymakers in the education and general industry sectors redesign stress policies and measures to prevent stress.

Keywords: Machine Learning, Stress Management, Deep learning, Stress factors, Technology, COVID-19

1. INTRODUCTION

Stress is a condition of physical or mental strain that might result from unavoidable experiences or ideas and cause agitation, anger, or dissatisfaction.

It may be advantageous if it keeps a person aware of their surroundings and ready for peril, but it can also be detrimental if the stresses persist for extended periods of time without providing any respite.

Stress levels have gone up recently because of things like housework, online learning, and COVID-19, particularly during the epidemic. Stressors may take many diverse forms, such as events in life, physical changes, alterations in the environment, and social pressures. Stress prediction has been made simpler with the development of machine intelligence methods like support vector machines (SVMs) and linear discriminant analysis (LDA). Probability theory is used by Naive Bayes, gradient boosting is provided by Extreme Gradient Boosting, and schizophrenia is classified using Random Forest.

Image processing and data mining have made use of deep learning methods such as Convolution Neural Network (CNN), Artificial Neural Network (ANN), and Recurrent Neural Network (RNN). While LSTM has been used to address mood prediction difficulties, CNN is a terrific deep machine learning technique for assessing psychological duress confronted by college students.

It is essential to speak about the underlying causes of tension in order to address stress management. The elements fell into four categories: factors linked to COVID-19, factors related to the workplace, factors related to education (students), and factors related to education (teachers). Interpersonal, psychological, personal, and work-related elements are included in each category. Developing successful stress management techniques requires overcoming tension.

In summary, the primary contribution of the work is as follows:

- Several machine learning and deep learning-based stress/prediction algorithms are identified in our thorough analysis.
- The paper lists a number of stressors and discusses how they affect automated stress prediction and deep learning in the corporate and academic domains.
- The article also looks at how people's overall stress levels have gone up as a result of technological advancements.
- The paper also covers the research on stress that was done during the COVID-19 pandemic.

Our thorough examination of stress management gives particular weight to people's techno-psychological aspects. To put it another way, it covers more than only the technological components of identifying stress using intelligent approaches such as deep learning and machine learning, but it also offers a list of several factors that contribute to stress, as well as the sources of stress and the impact of technology fear on stress.

The paper will provide educators, legislators, and businesspeople a perspective on how to implement suitable methods and uphold best practices of stress management in academic institutions and companies.

2. LITERATURE REVIEW

Murphy et al. (1984) outline all the advantages, requirements, and methods of stress management as well as stress management strategies. Lawrence R. Murphy, "Occupational stress management: A review and appraisal." 57, no. 1 (1984) Journal of Occupational Psychology: 1–15. Studies by Greenberg et al. (2002) assessing the benefits of workplace stress management and outlining Comparing workplace stress management research based on program direction and structure, work group type, stress management techniques, non-specific effects, and long-term skill and benefit maintenance J.S. Greenberg, 2002. thorough stress reduction.

Bryant et al. (2016) emphasize both the contrasts and the similarities. Boss, P., Mancini, J.A., and Bryant, C.M. (2016). Stress management in families:

A situational approach. Sage Books. Murphy and associates (1996) combinations of stress-reduction strategies combined into a single intervention L.R. Murphy, 1996. An analysis of the detrimental impacts of workplace stress management on health. 11(2), pp. 112-135, American Journal of Health Promotion.

STRESS MANAGEMENT & MACHINE LEARNING PROGRAMME

In both smaller and larger populations, machine learning models help in the identification, assessment, and prediction of stress. By teaching participants how to react to stresses more effectively, these models are employed in stress management programs, which helps participants feel less stressed overall.

Management of stress courses that interact with these sorts of gadgets and apps should continue to develop in size and number. The wearable health gadget and fitness platform industries are driving the popularity of health-related applications and devices.

Effective stress management improves people's quality of life. However, machine learning programs can analyze massive quantities of data, usually biometric data, to help in this attempt. These models are able to identify stressors, their levels, and the most effective ways to relieve stress in a given individual. They can even project stress levels in the future.

Furthermore, these programs may provide stress-reduction strategies that work well for a certain group of people before changing their suggestions for the individual.

MAP OF CONCEPTS AND SEARCH PARAMETERS

First, we developed a list of keywords linked to stress management. As mentioned in the opening section, we have limited the scope of our analysis to the education and employment sectors in order to prevent scope irrelevance. It was found that most stress management strategies are based on static characteristics. We also found that the primary causes of stress-related issues are challenges with money and work. The conceptual map is shown in depth in Fig. 1.

Search criteria for a systematic review include searching the Scopus, Web of Science, and Google Scholar databases for relevant publications. Papers are found using a variety of search terms, including "Stress Management," "Stress Level + ML," "Management of Stress with Machine Learning," "Management of Stress with Deep Learning," "Detection of Stress with Machine Learning," "Detection of Stress With Deep Learning," "Stress Detection + Deep Learning," "Stress management + COVID," "Stress management + education," "Stress management + Work environment," "University stress levels in COVID 19," "Employee stress management in COVID 19" and "Stress management in COVID 19" among others.

This thorough survey on stress management addresses the following study questions:

- What are the different methods for identifying and predicting stress that use deep learning and machine learning to help manage stress?
- What Affects Stress and How Does It Affect Employing Intelligence Technologies for Automatic Stress Prediction in Education and the Workplace?
- Does the advancement of technology lead to a rise in stress levels among people as a whole? How?
- What effect did the COVID-19 pandemic have on a person's elevated stress threshold? How?

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Stress detection and prediction techniques using deep learning and machine learning:

hese days, stress plays a significant part in the emergence of several illnesses that negatively impact a person's social, mental, emotional, and physical health. Data from the American Institute of Stress indicate that around 33% of individuals report experiencing extreme stress . This is a noteworthy number that warrants careful consideration. Thus, in order to prevent this awful threat before it emerges and reaches, it becomes necessary that we develop methods, build systems, and use the proper techniques in the appropriate manner to detect stress at an early stage.

In the past, performance assessments that focused on the person over lengthy periods of time, physical examinations, brief mock trials, and questionnaires were used to identify stress. These methods were particularly person-centered, limited, and focused, all of which had an effect on the measures' objectives. Because the early methods relied on a person's replies for mock-up and questionnaire rounds, as well as health-oriented inquiries for medical testing, which also depended on the time the samples were acquired, they were influential and prone to human error. These approaches lacked accuracy and transparency. Consequently, there was a need for modern methods and tools to deal with the stress issue successfully.

Currently, there are technologies, techniques, protocols, or algorithms that are able to precisely, reliably, and correctly pinpoint the underlying causes of stress and provide widespread relief from it. This section outlines the strategies that may be used to manage stress.

In recent times, one of the main techniques for stress detection has been machine learning, which may be either supervised or unsupervised. Supervision and learning from these experiences is the most popular approach to healing mental health concerns. The most popular techniques are SVM (support vector machines), decision trees, and neural networks. All three algorithms are capable of preventing overfitting and have an accuracy of over 70%. A decision tree is a method of decision-making that uses a tree structure to determine the answers for certain problems. It's one way to show an algorithm that just makes use of conditional expressions and control. Decision trees are often used to assess a person's level of stress or susceptibility to stress by closely reviewing a number of indicators. A person's mental state and level of stress may be ascertained from the original facts, even if they are subjective in nature. Subjective data comprises details from sources such as Electronic health records (EHRs), electronic clinic records (ECRs), Reddit, and interviews. In order to have a comprehensive theoretical understanding of the terms, this data can then be pre-processed using various NLP (Natural Level Techniques) like lemma, POS (part of speech), and CUI (concept unique identifier). These techniques identify the key words associated with stress, such as tension, depression, mental pressure, and many more. After that, the linguistic data must be converted into numerical data so that the values may be found using a variety of classification techniques, including DT, Logistic Regression, and SVM.

The machine learning method known as linear discriminant analysis, or LDA, was used to classify a situation as either stressful or not. The naive Bayes method uses probabilistic theory to solve the categorization issue. Given that B has previously occurred, the probability that A will occur may be calculated using the Bayes Theorem. In this case, B is the evidence and A is the hypothesis, assuming that the predictors and characteristics are independent.

One of the fundamental techniques for applying probability to classification problems is logistic regression, but it makes use of a more intricate cost function called the sigmoid function. Independent data (x) are linearly blended with weights or coefficient values to anticipate an output value (y). A family of linear algorithms known as support vector machines (SVMs) is useful for many different kinds of tasks, including as novelty detection, regression, classification, and density estimation. SVM uses categorization techniques to build a prediction model. A hyper-plane in an N-dimensional space that unambiguously classifies the data points is sought for using the SVM algorithm.

SVMs are a great tool for classifying stress into various levels according to severity, such as low (manageable), medium (under concern), and high (urgent action required), when used in combination with the process of processing data in line with the suitable classification approach. To estimate the degree of stress or pressure, the classifier employed data collected from several sources organically, in vivid scenarios, and while driving, such as breathing, finger temperature, skin temperature, GSR hand, heart rate, and EEG. Next, the data was divided into 100, 200, and 300-second time periods. After all of the mathematical characteristics were eliminated, the separator was then loaded with the remaining ones. Finally, SVM was used to establish that the pressure was obtained with 99% accuracy in 300 s and 98.41% precision in 100 s and 200 s simultaneously.

The term "XGBoost" refers to Extreme Gradient Boosting. A prediction model is produced from a collection of weak prediction models, often decision trees, using gradient boosting, a machine learning technique for classification and regression issues. Similar to other boosting approaches, the method builds the model step-by-step and then allows for the optimization of any differentiable loss function.

Many deep learning approaches have been used in image processing and data mining applications. Convolution neural networks (CNN), artificial neural networks (ANN), and recurrent neural networks (RNN) are the most popular deep learning techniques. Stress detection has been achieved via the use of triplet loss function deep neural network methods.

The neural network's input layer, hidden layer, output layer, and connection weight are all included in the design of the brain model. In the buried layer, processing that converts input into output occurs. Connection weights are stated as the input's relative strength. Every node in the input and hidden layers has a transformation function in addition to a summation function. The input layer has nodes that represent the input variables. The output layer now shows the output variable of a prediction issue.

CNN s' is an excellent deep learning method for quantifying the psychological strain that a large number of college students face. To produce the intended output, the ECG signals must first be obtained using an ECG signal collection device. Subsequently, the wavelet transform technique has to be used to denoise the collected ECG data. The sequential backward selection method is then used to choose the psychological stress indicator features in order to minimize error, decrease the feature subspace, and improve computing efficiency. Ultimately, a convolutional neural network-based recognition model for mental pressure indicators is developed, and its parameters are fine-tuned to extract the mental strain indicators of university students. In the past, mood prediction problems have been addressed using the long short-term memory (LSTM) network, an enlarged structure of the recurrent neural network (RNN).

There are more than 100 pupils that endure exceptionally high levels of stress and sadness, despite the fact that each mental health problem is assessed using a distinct model, algorithm, and feature selection procedure. It follows that it is considered that pupils have no idea what the future holds. The most effective model to identify stress is a choice tree, including the following six elements: religion, leisure, positive emotions, memory, negative emotions, and interpersonal relationships.

Due to individual variations, we often run into problems when we train generalized machine learning models using human data: the data distributions may vary from participant to participant. Two people with comparable levels of well-being may use their phones in different ways, which might cause disparities in feature representation and internal covariate changes across datasets. Therefore, we propose an LSTM structure that includes batch normalization (BN) to reduce participant heterogeneity.

Deep learning makes substantial use of convolutional neural networks (CNN), especially in the field of computer vision applications. Using filters (convolutional kernels), CNNs can precisely capture the temporal and spatial correlations present in a picture. By combining the above two concepts, timestamp dependencies may be used by CNN and RNN to extract characteristics from data. The high-dimension feature space in which our data is located raises the possibility of over-fitting of the training models. With CNN's convolutional kernels, we can actively extract high-level features from our high-dimension data.

The CNN-LSTM model performed worse than the deep LSTM model in participant-independent wellbeing prediction. While all four algorithms—SVM, DNN, CNN, and XGBoost—performed well in stress prediction, CNN outperformed the others.

While there are several machine learning methods available for stress prediction, the underlying principles of all the solutions remain the same. No matter how differently the output of each individual technique utilized is presented or how differently it differentiates between various degrees of stress, the end result's significance remains the same in every situation. As a result, the following processes are used to identify stress using different machine learning techniques:

Step-1: Dataset for Stress Input: Data on stress is collected in the first phase from several sources, such as performance-related data, questionnaire sets, and brief mock test rounds. Based on the explicit demands of the user, the dataset is assigned characteristics and class labels. Factors such as the level of study pressure, instructor conduct, school climate, and so forth are important to take into account while evaluating a student. Nevertheless, these qualities are much less important for working professionals. Thus, just those factors that are relevant should be considered.

Step 2: Data Pre-Processing: In this step, data is filtered to remove any fields or characteristics that are not necessary for the stress detection procedure. The data is also subjected to null, duplicate, and missing value checks. Samples containing any of the above specified values will be removed from the dataset to avoid any unreasonable mistakes during the dataset's processing for prediction.

Stage 3: Train-Test Split: In the third stage, the dataset is divided into data for testing and training. Usually, 30% of the data is utilized for testing and 70% is used for training. With the use of training data, the model will discover how to differentiate between stress levels and establish threshold values for different scenarios. The trained model will be used on the testing data to look for over- or underfitting problems.

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Step 4: Stress Detection Model Implementation: The fourth step will include using the selected algorithm to determine stress levels based on inputs vivid qualities or attributes, depending on the kind of user being monitored.

Step 5: Performance Evaluation: To make sure the approach was applied successfully, the model's performance will be evaluated in the last step based on a variety of measures, such as accuracy, precision, F-score, and others.

Because of this, the fundamental design of all algorithms used for stress detection is the same.

EFFECTS OF STRESS-RELATED VARIABLES ON AUTOMATIC STRESS PREDICTION USING INTELLIGENT TECHNIQUES

The many factors that affect stress prediction and how they affect the automated stress prediction enabled by intelligent approaches are covered in this section. The elements have been separated into three categories: general, work-related, and education-related (student and teacher). classifications. Since all of the categories are covered in detail, many elements could occur in several categories. The list of stresses also includes interpersonal, psychological, work-related, and personal factors.

Broad Category: The stressors that are discussed here are ones that affect individuals, regardless of their professional credentials, and may make them feel stressed either directly or indirectly. Put differently, the topics covered here are universal and affect everyone in the same way.

Personal Factors: Important stress-related personal traits include age, gender, education, race, career, and nationality. These factors have little beneficial effect on performance and undermine the individual's morality. These traits have an impact on a person's form even if none of them are genetically based. These factors have an impact on social exclusion, violence, and prejudice against certain groups of individuals.

Section II:

Workplace Factors: It encompasses any workplace practices, circumstances, or problems that affect a working professional's output and productivity. Among the factors are experience, job position, and work-life balance. These factors are essential for work satisfaction. These, when used as a motivator, remove boredom by promoting creativity and fulfillment. When they perform badly, however, they lead to hostility and a lack of fulfillment in their employment.

Psychological factors: These are related to an individual's motivations, outlook, and way of thinking about life. Stress is a result of uncertainty in a scenario, and psychological stressors indicate how a person will act or react in that circumstance. Two of the most significant factors are despair and anxiety over the illness. These factors lead individuals to withdraw socially, cut down on their social network, and give up on a number of fun activities.

Interpersonal factors: These include how individuals relate to one other, including how well a person gets along with colleagues and peers at work or with instructors and students in higher education. These include issues caused by their friends, family, and older residents; verbal and psychological abuse being one of them. If we take a positive view of these factors, peers who are encouraging may help people do better; conversely, peers who push others negatively can cause them to perform worse.

Education-related factors

3. FOR STUDENTS

While stress in general is not new, the focus on stress among students is relatively recent. One major source of stress among students nowadays is overwork, which begins when they enter secondary school (and sometimes even during their basic education). Therefore, it's critical to identify academic pressures and respond to them suitably and on schedule.

Personal issues: These factors affect a person's inner self and lead to overthinking, which in turn produces stress. Examples include physical beauty, an addiction to the internet, insecurity, and self-desire. These are items that aid with self-awareness. Self-desire, physical attractiveness, and other characteristics are not particularly important. It is better for one's health to be happy than to have a fantastic figure. Low self-esteem and confidence might arise from being impacted by such problems.

Work-Related Factors: Because a person's educational environment and learning environment lay the groundwork for their future, it is essential to consider the environment in which they study and finish their education. Peer behavior, study spaces, competitive environments, and the relationship between teachers and students are a few factors that influence a student's academic success.

When seen favorably, factors like a fiercely competitive environment and a strong rapport between teachers and students may motivate students to do their best work rather than accept mediocrity. However, if these components are interpreted improperly, the learner experiences increased anger, insecurity, etc.

Psychological variables: they indicate a student's likely response to both prearranged and impromptu events, including randomly assigned mock examinations or exams, as well as scheduled events like exams, viva-voces, and practical assessments. Such situations must be taken into consideration since they could negatively affect a student's performance. A few examples are test anxiety, the fear of failing, getting bad grades, and finding learning challenging.

Interpersonal elements: Interactions between a student and his instructors, friends, and other significant people in his surroundings are considered interpersonal variables. These connections affect how students behave and work, which might eventually cause stress. A number of factors are involved, including crowded classrooms, bullying by peers and groups, and cohesive teamwork. These factors negatively influence the workplace and have a direct effect on an individual's educational environment. Learners who can respect others and sometimes inspire them are the ones we choose.

For Teacher:

Teachers shine a light on the lives of many children to provide them with the finest opportunity for a bright future. They provide us guidance, moral principles, etiquette, and counsel so that we may all be successful. We students sometimes fail to obey our professors, or rather, teachers, even if we give it our best. If it's not by our own fault, then maybe because of other factors like stress. Therefore, it's essential to understand and respond accordingly when necessary.

Individual differences: Teachers' effectiveness is hampered by these factors because they make them overthink and misunderstand their own skills or standards. Self-worth, attitude, managerial abilities, and aptitude for problem-solving are a few examples. The way a teacher is seen may have a positive or negative effect on the teaching process. A bad teacher will create a negative environment in the classroom that will hinder students' ability to learn. Conversely, students and instructors alike stand to gain when an educator adopts a positive view on life. It's critical to take the proper steps at the right moment.

Factors at Play: Among these factors are situations that cause emotional, psychological, or bodily discomfort at work and put educators under stress. Among the contributing causes include long work hours, job insecurity, a depressing work atmosphere, and strange conduct. Numerous variables influence teachers' efficiency and productivity, which in turn influences their job happiness, sense of teamwork, absenteeism, etc.

Psychological variables: These factors influence how instructors react to real-world occurrences or fictitious yet stressful circumstances in terms of their attitudes and behaviors. These components include a delay in material supply and mental exhaustion. Teachers' health and wellbeing are being negatively impacted by high concentrations of these factors, which leads to burnout, disengagement, the highest turnover rates, etc.

Interpersonal Elements: It incorporates social characteristics, behavior related to instructors, the kind of pupils around them (i.e., students), and receptivity to group discussions and cooperative activities. Among the reasons are teamwork, emotional intelligence, and good communication. The organizational culture is directly impacted by these factors. The ineffectiveness of these factors harms the workplace. More individuals need to exist who can sometimes understand and motivate others

Elements related to the workplace: Offices are the hardest places to work and thrive. In addition to workload or job pressure, there are a number of environmental, social, and unique factors that affect stress in corporate offices and workplaces. It is crucial to define and characterize them as a result.

Personal factors: These include things like a working-class worker's or professional's identity. A person's performance and productivity for the company are adversely affected if these factors are not considered in advance. Examples include personal inadequacies, rank or classification, and internal conflict. In such situations, workers find it difficult to concentrate, make decisions, and feel confidence in their work. Additional repercussions include emotional issues, absenteeism, and an imbalance in work-life balance.

Work-related factors: These factors mostly concern the person's workplace and any difficulties or problems they run into when they are employed. A few examples are the amount of work, working relationships, control of the task, and inadequate member coordination. These factors raise the possibility of errors, poor job output, exhaustion, mental health concerns, and workplace difficulties for an employee.

Psychological factors: These explain how professionals in the workforce react to and interpret situations that are both official and informal. Stress, anxiety, and depression are a few of the contributing factors. Workers with psychological illnesses are more prone to struggle with anxiety, depression, and sleep issues, all of which have an impact on their productivity and job satisfaction.

Interpersonal Relationships as Factor: These include an employee's ability to get along with their supervisor, other employees, and other team members or group members while working on group projects. These attributes also include

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the manner in which colleagues and elders conduct and think in social and professional settings. Interpersonal disputes and a rise in duties are two examples. These factors have a direct impact on working conditions, work-life balance, and the workplace. Because it gives workers control over the stress caused by external factors, it could be seen favorably outside of the workplace.

IS A PERSON'S OVERALL RISE IN STRESS LEVELS RELATED TO THE ADVANCEMENT OF TECHNOLOGY?

Modern communication technology has made our lives simpler. For instance, things that used to take weeks to happen on the other side of the globe may now happen in a matter of minutes or seconds. They have, however, quickened their speed of travel. Because modern technology has permeated every aspect of our life, it is easy to become too dependent on it and experience a range of negative effects. The purpose of this research is to investigate how technology has impacted our lives and raised people's overall stress levels. First of all, it has been shown that utilizing information and communication technology, or ICT, may lead to feelings of anxiety, worry, and stress in users.

This issue is described as "techno-anxiety." Second, consumers could have psychological consequences that make them feel less self-assured. Powerlessness, discomfort, and the disorder known as technophobia—an aversion to or fear of using computers—can result from such circumstances. Thirdly, over reliance on ICTs may lead to a condition known as techno-addiction. Last but not least, the inability to cope with modern computer technologies in a healthy and productive way has resulted in Technostress, a malady of the contemporary period of adaptation.

Social networking sites, or SNS, are largely to blame for the rise in the prevalence of the aforementioned diseases among individuals today. A growing number of individuals are using the internet to access many aspects of their lives, which presents a lot of problems to self-control. SNSs allow users to interact with others who have similar interests by allowing them to upload pictures, videos, and other data about their life and to reply to postings made by other users. SNS use may rise along with the adoption of ICT devices such as tablets, smartphones, and desktop PCs. There is evidence that excessive usage of social networking sites—defined as more than two hours per day—is linked to poor mental health, increased psychological discomfort, and suicide thoughts, in addition to being potentially harmful and addictive for a tiny number of individuals. For people who fit into this group, the terms "SNS addiction" and "problematic SNS use" (PANSU) accurately characterize their use of social media as an engaging hobby that takes up all of their mental space. It is motivated by a strong, often pathological demand to utilize or access social networking sites. The individual ends up devoting a significant amount of time and effort to SNSs as a consequence. This has a negative impact on work/study, other social activities, interpersonal connections, and/or psychological health and well-being. Further investigation also showed that the stress caused by social networking site addiction has a role in the symptoms of mental disorders, including OCD, anxiety, ADHD, depression, and stress.

Technology usage has been connected to major health problems, including sleep disturbances. Furthermore, a number of scholars have investigated the variables that forecast procrastination while using technology and the internet. "Failure of self-regulation or not exerting enough self-control for task management" is the definition of procrastination. Notably, children with poor self-control and reduced self-directed learning have been shown to often utilize social networking sites in an unregulated and probably procrastinatory manner. This is due to the fact that SNS, as opposed to significant but tedious academic assignments, may provide transient guilty pleasures via the experiences and enjoyment of certain activities like gambling, pornography, etc. To sum up, we can say that using the internet intermittently negatively affects many aspects of functioning, including social, family, academic, professional, and personal life.

Due to the growing workload, educators are required to incorporate technology use into their pedagogical techniques in the classroom. This causes an overwhelming burden, difficulties, and stress for educators. Teachers are often at a loss for what to do because of their limited time and the increasing demands of schools and institutions. It has been quite demanding and challenging for the instructors to stay up to date with the developing technology and the innovations associated with them. Many instructors lack the skills and abilities needed to effectively utilize technology for lesson preparation, information delivery, and student recruitment, despite the fact that they may see it as such.Conversely, organizations have increased their ICT spending. As a consequence, advantages for companies and workers have been found, although certain disadvantages have also been mentioned. Traditional workplace stress is replaced with mobile workplace stress—which involves increasing employee engagement to support them in carrying out their responsibilities, improving individual performance, and achieving organizational objectives—by changing the internal structure of the enterprises. These technological stressors are also associated with detrimental psychological outcomes such as increased role stress, decreased work satisfaction, and decreased organizational commitment. A subpar information system (IS) also causes employees to be less creative in their work, less productive while using the IS, and dissatisfied with the IS.

Students are finding it hard to focus due to the pandemic's emotional effects, which may also have an impact on their health and capacity for independent learning. This is true for kids in both college and high school. Of the 3670 medical students polled, 93% had a smartphone and 83% possessed a laptop or desktop computer. Just 19% of the students utilized prepaid mobile data to access extra online resources, compared to 79% of students who had a postpaid internet connection. Among all the obstacles, the most common ones were adjusting to different learning styles, managing responsibilities at home, and unclear or inadequate communication from teachers. After encountering these challenges, their workload increased.

It is evident that sensed apprehension and anticipation confirmation had a significant role in influencing the decision to use mobile learning. Furthermore, prior research demonstrated the potential advantages of using mobile learning (ML) in the classroom during the pandemic for both instruction and student learning. This impact may be mitigated by the fear of losing friends, a demanding household, and concerns about future academic achievement. In order to prepare students for emotional and mental resilience, it is imperative that assessments be conducted appropriately before, during, and after the outbreak.

4. DISCUSSION AND CONCLUSION

Literature Contributions

Stress always appears like an abstract idea, but in reality, it impacts a lot of people today, either directly or indirectly, depending on their social, professional, personal, and demographic characteristics. If stress is not identified and managed early enough, it may have detrimental effects. There are already a number of machine learning (ML) models available to predict stress, and to improve the accuracy of stress detection, more advanced techniques are being used. Thus, it is evident how crucial stress management is in the cutthroat world of today. We attempt to provide an overview of the contributions that the models and ML approaches that have been presented in real-world contexts have made.

A few scenarios where stress detection could be essential are as follows:

- Stress detection models may be used to predict stress in school and college students early by using stress scaling scores based on a series of questions related to the activities that students completed.
- Working professionals spend most of their time in workplaces, and they often take part in demanding team projects or activities. The pressure to do better than others might put them in stressful circumstances, which can lead to overthinking and negative health effects. Systems that monitor every action workers perform while at work throughout the day using a range of models are being incorporated.
- In fact, stress prediction is receiving attention as a way to help the healthcare industry since stress and anxiety play a big role in neurological and cardiovascular problems. Health monitoring devices have integrated stress detection and monitoring systems to measure stress.

Implications

The effects of the pandemic in the modern period have brought everything to a halt, particularly since the modern era has expanded. Every sector was negatively impacted, and it is reasonable to assume—and to conclude based on the research studies and results mentioned above—that people's stress levels suddenly increased to previously unheard-of levels. Following an unanticipated turn of events, people from a variety of backgrounds and professions found themselves at home attempting to keep the work running.

The primary objective of the comprehensive review was to closely examine each individual's occupational background in order to identify the best stressors affecting that specific class of people and tailor appropriate techniques and methods to achieve the desired outcome. to look into and understand the underlying cause of the issue and potential effective stress management techniques. Maintaining integrity, objectivity, and consistency, the focus was on assessing a variety of groups as a whole according to the most important factors that cause stress in each of them. In order to understand the process of selecting the top traits that significantly contribute to people's emotions of stress based on various demographic, social, educational, and professional aspects, we ran it through a number of machine learning algorithms. The mathematical and statistical outcomes of these techniques have proven to be very advantageous as they have enabled the most precise identification of stress levels over prolonged durations by using a preset criteria that is set at the start of training.

As was previously established, technological advancements have made life simpler. Technology has made it easier to plan, communicate, and educate, but it has also increased workplace and student stress. Everyone who was remaining at home during the epidemic had joined the younger generation, who was already actively immersed in social media. It was also observed that social media often had an unbiased tone.

Proposed next steps

The research focuses on the education and industrial sectors since they are the ones that experience greater levels of stress. When searching on sites like Google Scholar, Scopus, ERIC, and Web of Science, the bulk of the documents on stress were located in the two regions listed above. Our thorough analysis of stress management focuses on the techno-psychological aspect of the human person. Put another way, it covers the technical components of detecting stress using sophisticated methods like deep learning and machine learning, but it also lists a variety of factors that influence stress, including its origins and effects, as well as the relationship between technology anxiety and stress.

This essay will provide a case for educators, legislators, and business leaders to implement the necessary policies and uphold industry standards for stress management in organizations and workplaces. Soon, the same discussion may be extended to other sectors of the economy, such as healthcare and banking.

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