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Clinical Diagnosis of Chronic Stress Using Bio-Signals Within the Framework of Industrial Revolution 4.0

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Abstract: New proposals and tools provided by Industry 4.0 and the elements of intelligent classification have removed the barrier to analysis of previously unmeasurable conditions, such as stress and the emotional spectrum. Stress is a well-known condition in industrial work environments and although it is a necessary biological function, in high doses, it becomes a chronic condition capable of triggering dangerous diseases. This paper seeks to show an approach to the smart technological diagnosis of chronic stress within a workplace environment, with the goal to promote compliance of new norms of worker welfare that are found within the social section of Industry 4.0. In this context, we discuss both acute stress and chronical stress. Acute stress is the common stress found for a short period of time when the body needs to adapt to an unknown or unexpected situation; in contrast, chronic stress is present as a result of constant stressful stimuli and becomes the body's new norm. To accurately give a clinical diagnosis for chronic stress in an industrial environment, a full framework for emotional detection with a real-time diagnosis approach is required, as is referencing a practical case of study for industrial applications. The result of such analysis is a better understanding of the current challenges and opportunities, as well as tools for a more human oriented company all in a full technological cybermedicine diagnosis.

Keywords: Mental Stress, Bio-Data, Industry 4.0, Stress Diagnosis

1. Introduction

Working conditions have changed greatly in the last 20 years. Several factors, such as wide spread automatization, mass internet communications, and new technological and social broken work paradigms, have disrupted a pre-stablished understanding of how employees interact with their working conditions on a physical and mental level (Vicente et al., 2015). Such reaction to new stimuli reinforces a trend within social and technological research branches to comprehend and muffle any cause or consequence that could negatively affect the development and performance of companies' workforce (Leka et al., 2004). Of all the possible emotional phenomena which can impact adversely on an employee's performance, mental stress occupies the spotlight as a common and extremely dangerous condition for any worker. Working stress conditions have gained such notoriety in companies that governmental actions have asset the situation in multiple countries, as in Mexico, where not one but two national laws have been created to address work stress conditions in a productive (NORMA Oficial Mexicana NOM-035-STPS-2018, Factores de Riesgo Psicosocial En El Trabajo-Identificación, Análisis y Prevención., 2018). Based on what's been mentioned before, it is necessary to realize that stress is an intrinsically subjective condition, meaning that it varies greatly in each individual. So, how can you confirm that stress is present in an employee; more importantly, affirm that a worker is chronically stressed and it's caused by the work load? Therefore, such questions, a deeper analysis of emotional recognition systems, their industrial environment applications, and reliability for clinical diagnosis must be done to approach a company implementation and mass compliance of normative shown before.

1.1 Acute and chronical stress

First, in order to understand the basis of emotional diagnosis, a comprehension of the main emotional condition is needed. For this paper, the mental stress phenomenon is the main mental hazardous condition to analyse. Because of this, a basic grasp of mental stress theory is required. Based on the last idea, we can define mental stress in a simple manner as a mental awareness state of mind due to a reaction to unsuspected situations (Giannakakis et al., 2019). Therefore, mental stress can be triggered in most environments and be received by most living creatures. Although naturally present in every living organism, stress is a condition that suffers in greater quantities and becomes a chronic condition, which can become a trigger for more complex and dangerous states for the human body (Al-Shargie, 2019). Furthermore, experts and previous research consider two kinds of stress acute stress and chronical stress (Castellanos et al., 2017; Kim et al., 2018). The first one explains stress that is caused by a single strong stimuli, for example, an unexpected news, a loud noise, a minor fall, etc. Commonly, acute stress consequences are not long term but temporal, meaning that the human body will change only to react to such a stimuli. Obviously, due to its characteristics, acute stress is not considered a clinical condition but a status quo of life itself. Continuing with chronical stress, it is important to mention first that this condition is not a separate framework of reaction based on different stimuli, but a consequence of prolonged acute stress (Giannakakis et al., 2019). While acute stress by itself is mostly harmless, at the time when its recipe is in greater quantities and extended periods of time, it becomes a dangerous clinical disorder. Such sustained exposure to prolonged acute stress is known to be a trigger for heart and mental illness (Alberdi et al., 2016). Consequently, it should be noted that both kinds of stress can be detonated by similar or equal stimuli, creating a challenge as well as an opportunity to understand, measure, and diagnose stress in a wide range of environments and users.

1.2 Stress in workplace

As shown before, there is an undeniable relationship between stress and environmental stimuli, which has been the direct cause of all kinds of stress. Now, concentrating on workplace settings, it is prudent to affirm that most structured work environments can be extremely stressful, especially those industries which are in constant change by adapting to new processes, technologies, protocols, laws, and last but not least, constant and complex problem solving (Thapliyal et al., 2017). Then, it comes as no surprise that many industrial workers suffer from a high rate of stress. Consequently, the main threat comes from the normality of such a stimuli; but, not even chronic stress is an immediate death condition. Due to this fact, stressful stimuli at work are rarely approached by norms or regulations, nor by immediate commands or supervisors(Gross, 2017). However, there are conditions which are steadily present in decision making level environments within many companies and can't be ignored, such as strokes and heart attacks. Likewise, all those health conditions have a common factor: workplace stress, although not the only one (Macias-Velasquez et al., 2019). There is a connection between stress and critical chronical affections. This link gives a justification for preventing and evaluating the stress load on the working personnel of a company. Nevertheless, it's important to mention that stress is an emotional reaction based on perception. Because of this, measuring stress trends is highly difficult and depends greatly on how it is analysed and by who (Panicker & Gayathri, 2019).

Generally speaking, by demand of health organizations and mostly in countries with high levels of stress due to workload (such as Mexico, China, USA, etc.), companies and governments have approached the situation of managing work stress within their working population. As an example, Mexican Norm 35 became a must after research revealed that eighty-five percent of Mexican organizations do not have the appropriate conditions for their employees to have a balance between personal life and work, which leads to stress and physical and psychological disorder (NORMA Oficial Mexicana NOM-035-STPS-2018, Factores de Riesgo Psicosocial En El Trabajo-Identificación, Análisis y Prevención., 2018). Likewise, 4% of GDP is lost annually due to stress (Madero Gómez et al., 2020), depression, and anxiety generated by work, hand in hand with work accidents. Consequently, Norm 35 is a recent law approved in Mexico which is also called the "stress law". This law's objective is to establish the elements to identify, analyse, and prevent psychosocial risk factors, as well as to promote a favourable organizational environment in the workplaces. Then, NOM-035 applies throughout the Mexican territory and applies to all workplaces and companies (Madero Gómez et al., 2020). However, the provisions of this standard apply according to the number of workers who work in the workplace. As a result of non-compliance with the regulations and resulting in behaviours or omissions that involve risks to the health, life, or safety of employees, Nom-035 indicates the application of fines (NORMA Oficial Mexicana NOM-035-STPS-2018, Factores de Riesgo Psicosocial En El Trabajo-Identificación, Análisis y Prevención., 2018). Furthermore, similar standards are in force in other countries and also require full compliance. In summary, these kinds of laws focus on companies that have dangerous and unsafe working conditions, incur excessive workloads, have hours and rotation of shifts that exceed what is established in labour laws, have no proper work-life balance, have negative interactions in the work context, and have cases of workplace violence (physical harassment, psychological harassment, and mistreatment).

1.3 Industry 4.0

First, it’s imperative to talk about the new revolution which is changing the industrial environment forever. Industry 4.0, also known as the fourth industrial revolution, refers to a change in the work framework which is characterized by an increase in the use of automation and smart factories technologies(Vaidya et al., 2018). Such changes are made to obtain information from real-time data to improve efficiently and productively from an operative level to a strategic level. In addition, flexibility is also enhanced so that manufacturers can better meet customer demands by collecting more data from the shop floor and combining it with other business operational data, as well, enabling better decision-making processes to be made (Xu et al., 2018). Nonetheless, in order to achieve its proposals, industry 4.0 uses advanced technological pillars and tools. Therefore, some of the tools that support industry 4.0 are mentioned next (Vaidya et al., 2018):

- The Internet of things. First, the internet of things, or IoT, refers to a system of interrelated devices connected to the internet to send and receive information from one another, creating an information system that allows the company or user to have a real-time flow of relevant data.
- Cloud computing. In summary, cloud computing consists of the delivery of computing services directly from the internet, such as storage space, databases, networking, software, analytic applications, and smart systems.
- Artificial intelligence and machine learning. Truly, one of the most important factors within industry 4.0 is artificial intelligence. It consists of mimicking human thinking. This is done by using smart algorithms which learn patterns or characteristics of a system or phenomenon and later use that learning to modify behaviour. Although it may be the most extensive of all Industry 4.0 tools, most industrial problems only demand the subset of AI known as Machine learning.
- Edge computing is a networking paradigm that focuses on placing processing as close as possible to the source of data to reduce latency and bandwidth usage. In simple terms, edge computing means transferring fewer processes from the cloud to local locations, such as a user's PC, an IoT device, or an edge server. Bringing processing to the network's edge reduces network latency.

1.3.1 Anxiety and stress within Industry 4.0

Industry 4.0 urges highly automatic systems and more technical loads, creating a new challenging environment. One of those basic challenges is a general interface setting, which means having to use human-machine interfaces on a large scale, because most work is done by computer or at least an interface (Zezulka et al., 2016). For this reason, one major factor that can be addressed is the digitalization of work. Commonly known as the transformation of analogic signals to digital ones, digitalization has gained a new meaning within the economic framework of the Industrial Revolution 4.0. Therefore, digitalization of work, according to the Gabler economic dictionary, refers to the increasing use of digital technologies in company settings (Bonekamp & Sure, 2015).

Then, one of the consequential factors of digitalization on enterprises is the demand for constant internal and external network connections. This demand for connectivity makes it possible and sometimes mandatory for workers to be connected to such networks as well. Constant monitoring by using online platforms like video and chat changes greatly the way a worker spends working hours. For example, the Covid pandemic showed employers how many of their processes and requirements could be done by a non-present employee with online tools. This realization saved money and working space for many companies and gave them a new perspective on online workers, as well as the connectivity capabilities of the modern industry(Madero Gómez et al., 2020). Nonetheless, this distant work concept came with a heavy workload for workers, especially in high-demand industries such as manufacturing or sales and services, in which demands from customers and logistics tend to be non-resting. In addition, the capability of separating work from free time has blurred drastically because of the online digitalization phenomenon, which is leading to a drastic increase in daily stressful mental state (Madero Gómez et al., 2020). Furthermore, the workload in a traditional industry could cause a heavy amount of acute stress, but if you add such acute stress to a constant connection setting, it is highly probable that chronic mental stress will develop. Added to such a stressful life setting, relaxation proves to be really hard in a mass-connected environment, due to the difficulty of unplugging.

As mentioned before, there’s a clear relationship between anxiety from being in a constant connection with the workplace and the constant use of digital devices and interfaces (Yıldırım & Solmaz, 2020). Nonetheless, this relationship to anxiety is increasing because of generational barriers, as well as the technical level of users and workers. As a result, some research suggests that employees not used to constant use of digital technology (for example, employees doing hand work or repetitive low-flexible actions) have an increased difficulty adopting new Industry 4.0 measures, directly and indirectly affecting their emotional health either by increasing anger, frustration, boredom, awareness, or even by overstimulation. Therefore, such un-balanced emotional stability creates a perfect set for stress and is gradually becoming a common state of mind (Leka et al., 2004).

Based on what has been said before, it is safe to affirm that Industry 4.0 has natural conditions and requirements that can become stressful if they are wrongly managed. Due to the fact that work is a common and routine task, it is almost certain that any mental stress condition will trend to become chronical. Then, based on the previous idea, it’s important that any approach to detecting and treating any emotional unbalance due to stressful conditions in work environments is based on the same Industry 4.0 framework.

2. Diagnosis and detection

First, we must recap emotions are perceptive phenomena. Therefore, such a property makes it hard to diagnose or detect a specific emotion. Then, to generalize an emotion range within a group presents an even more difficult challenge. Because, as mentioned before, the difficulty of detecting an emotion is shared by similar emotional phenomena such as stress. Consequently, diagnosing stress in the traditional way is done by surveying critical factors and a posteriori analysis by a medical/psychological specialist. For example, recalling the case of NOM 35 in Mexico, one of the solutions given by the government and industrial representatives was the creation of an evaluation index. Such a tool is filled out by an employee and evaluated by the local medical organization(Cazares-Sánchez, 2020; NORMA Oficial Mexicana NOM-035-STPS-2018, Factores de Riesgo Psicosocial En El Trabajo-Identificación, Análisis y Prevención., 2018). While the protocol is, in theory, pretty simple and straight forward, it requires the medical system to work properly and for an affected employee to be able to answer the index. In contrast, recent advances in machine learning and intelligent algorithms have allowed us to maximize the capabilities of biometric sensors, granting new lecture capabilities for emotions, stress and anxiety. Despite this, as mentioned before, such systems require advanced programming algorithms as well as some control over external and internal variables (Kumar et al., 2020; Manjunath, 2021).

2.1 Stress Diagnosis

Certainly, stress as an emotional phenomenon presents intrinsic challenges for any kind of diagnosis. In order to solve this problem, different approaches are recommended, such as a multi-test (Leka et al., 2004). Hence, not even medical personnel can diagnose stress based on a single factor, attribute or symptom. For example, while analysing a worker at a manufacturing company, he suddenly starts to feel anxious, increasing his heart rate and sweating. According to many standards, this is a natural stress reaction, but it could also be due to the emotion of a positive event, such as lunchtime or a congratulation, etc (Alberdi et al., 2016). The main point here is that emotions work in ranges due to the fact that some biological changes can be attributed to several emotional conditions (Sharma et al., 2020). High blood pressure, for example, in an emotional diagnosis can be attributed to anger, sadness, as well as more direct analysis (like phycological analysis) (Hassani et al., 2018). Therefore, it is important to analyse all possible variables, internal or external, for stress diagnosis. For example, in order for a qualified physician or medic to diagnose stress, biological phenomena such as heart rate variability and certain illnesses such as headaches or involuntary chronic movements must be checked, not limited to those markers. The revision must include questions about the routine environment, customs, diet, recent life events, etc. Overall, such measures are taken to reduce the potential bias for emotions and chronic conditions which share the same emotional spectrum. Because of this, it is prudent to affirm that the more information is gathered, the more precise the result of the diagnosis will be.

2.1.1 Environmental Bias

For this document, it's necessary to remind that the focus of stress diagnosis is oriented only to an industrial working environment, because of this, one of the main factors in detecting stress in industry 4.0 companies is environmental bias. Then this bias can be considered as the one that originates from the stressful environment but externalizes to another one (Alberdi et al., 2016). This means that if an employee is stressed at home and by the time he is in the company, the effects become acute. At the moment the employee is diagnosed, it can be inferred that the stressful condition was received in the working area. For this reason, a broad analysis is always demanded and also a certain knowledge of employees' routine must be inferred. Another way that the environment can affect stress detection is through critical stimuli. First, let's understand that stimuli per se is not entirely bad (Giannakakis et al., 2019). How the subject receives and adapts to them is the main factor in stress handling, but there's no question some stimuli could be harder to manage than others. For example, changing a machine setup with urgence is not as demanding as almost cashing in a car. Therefore, the level or strength of the stimuli works as a bias as well. Consequently, if a worker has a low stress balance environment in their company, but he suddenly experiences a dangerous or really stressful situation, any measure of analysis will be terribly prone to a wrong diagnosis.

2.1.2 Emotional bio-signals

As mentioned before, diagnosis of stress demands input data which will obviously be obtained within the system that conforms to the human body (Giannakakis et al., 2019). Therefore, all the signals that can be read from the human body are considered bio-signals. Although bio-signals can be almost unlimited, we can classify them based on their natural presence or existence. This means that if such a signal exists without any external stimuli or it must be provoked, the dynamic nature of the bio-signal depends on how much time it takes for the signal to change(Kaniusas, 2012). As mention before, there are some bio-signals that can useful for emotional and stress recognition, next in a listing some of the most popular bio-signals for stress diagnosis: Heart Rate (HR), Heart Rate Variability (HRV), Galvanic Skin Response (GSR), Electrocardiogram (ECG) and Electroencephalogram (EEG) (Giannakakis et al., 2019).

2.2 Common diagnosis methods proposed in Industry 4.0

As mentioned before, mental stress is peculiar and so is its analysis. For clinical diagnosis, many factors have to be reviewed in order to provide a prudent examination. Nonetheless, patterns in diagnosis can be observed and, to a certain extent, become mandatory (Alberdi et al., 2016). For example, no matter how the diagnosis is done, biological signals are used for diagnosis in order to divide it into possible biological causes and later classify relevant conditions, as well as an analysis of the stimuli, whether singular or chronic(Al-Shargie, 2019; Lindsäter et al., 2018). In general, due to the diagnosis being focused on the industry 4.0 framework, which translates to employee health as well as time and resources for companies (Van et al., 2021). There must be a special demand for reliable diagnosis, and at the same time, taking into account possible bias (mainly environmental ones) and the resilience or capability of handling stress and stressful conditions. Among the literature, there are two main tendencies in stress diagnosis which take into account an industrial 4.0 framework that can be identified, namely the physician approach and the technological approach.

2.2.1 Physician approach

So far, the common diagnosis for emotional phenomena is the traditional physiological one. In most any environment, orthodox or unorthodox, there is no question or discussion that an analysis of stress and anxiety is more mature within the medical discipline (Kalliomäki & Jansen, 2021). Therefore, any diagnosis provided by a medical expert has low probabilities of bias and misinterpretation; but, regardless of how good a diagnosis is, most of the time it is supported by equipment (Sioni, Riccardo and Chittaro, 2015). Medics use biological signals to support the separation of symptoms, allowing an extra backing of any analysis done to a subject and the consequential interpretation. However, as mentioned before, in order for an industry to give a direct diagnosis from a specialist as soon as possible, it must be a full-time company employee, thus requiring greater demand on the company in order to be rentable (Sioni, Riccardo and Chittaro, 2015).

The true minor point in classical stress diagnosis comes from practicality and quantity. Such a quality is becoming increasingly important in industry 4.0 (Krachtt, 2018), which mainly characterizes a more connected company and lessens the capability of disassociating from the work environment. Because of this, the use of evaluation formats and indexes as assets in the revision of a subject has gained strong use, especially in bigger companies. Although medical diagnosis can be really effective, it is also time-consuming and ineffective when checking large quantities of subjects.

2.2.2 Technological approach

In contrast to a more traditional approach, research shows that in order to detect and diagnose stress within Industry 4.0, it is imperative to support such a diagnosis within the same technology. Then, technological approaches include all systems which not depended of a professional physician diagnosis or depend in low measure. Some of the more relevant tools for emotional analysis, machine learning, and deep neural networks are based on the concept of learning (Ragot et al., 2018) and by supporting them with biometrical technologies, they can become a dominant trend for clinical diagnosis (Hamet & Tremblay, 2017). Then, any technological diagnosis needs an input system that consists of devices that register changes in biological phenomena through bio-data (Shin et al., 2018). Such devices are fairly common in medicine. Due to this, there exists a wide variety of equipment which can be used to detect and measure stress, although in medicine there's no mass-used equipment dedicated exclusively to this task. However, many proposed devices and methods have reached the prototype phase (E, 2019; Madan et al., 2018; Sioni, Riccardo and Chittaro, 2015) as well as shown significant results in obtaining biological data useful for emotional diagnosis(Giannakakis et al., 2019; Xia et al., 2018).

After the system of information acquisition, technological diagnosis continues by the processing of the input data. In addition, devices and methodologies hold several phases for signal processing, including but not limited to: signal filtering, imputation, classification. All the mentioned phases are oriented towards getting better information from bio-signal, which is mandatory when analysing complex systems such as the human body (Giannakakis et al., 2019).

Nonetheless, signal processing, although critically important, doesn't give an actual diagnosis, at least not compared to a clinical one. Because of that, the next phase of technological diagnosis uses several tools from Industry 4.0, biometrics methods, artificial intelligence, and cloud computing, to mention some (Van et al., 2021). All these tools help in getting the tacit knowledge implied in physiological traditional analysis into a technological one. First and more importantly, artificial intelligence. Although it is possible to assert certain patterns of detection during the classification phase in signal processing, emotions change considerably between people and stimuli (Sioni, Riccardo and Chittaro, 2015). Therefore, assuming a diagnosis based only on classical classification is un-efficient; here is where machine learning and deep learning come into play. These techniques specialize in autonomous learning, which allows them to get data patterns and behaviours that usually require a human mind to understand. While deep learning is widely used to mimic human understanding, it works really well when measuring non-numerical or range-base data. Next, machine learning is characterized by the use of mathematical models or methos to train the algorithm by using a dataset, and although it is widely used in biometric applications as an optimizer, it can also be used as an independent patter learner (Hamet & Tremblay, 2017; Manjunath, 2021; Subhani et al., 2017). Nonetheless, its use in combination with deep learning gets astonishing results(Zhang et al., 2020). This is because it increases reliability in analysis, and when managing human condition diagnosis, reliability weighs heavily on any criteria. Mentioned before, tools, combined with cloud computing, allows the use of large quantities of data without compromising data bases, give technological diagnosis a flexibility greater than ever before (Qi et al., 2018). Still, those tools depend greatly on knowledge of the system, for example in many devices or stress detection propose methods a conditioning time is requires, which means that in order to get a full stress diagnosis the user most deliver information for a period of time; it can vary between a couple of minutes to a day (Giannakakis et al., 2019). Furthermore, some uncontrollable bias like movement during diagnosis or a failure in the data acquisition system can create critical conditions that could affect the entire analysis.

3. Conclusion

There is no doubt that stress diagnosis has progressed in great measure in the last decade, but it seems like a goal-less advancement. Research and devices in both approaches (technological and traditional) are seen to be all over the place. Therefore, the matter of having the capability of reading and analysing stress is not critical. What’s truly critical is how you take those analyses in a cohesive way into the mainstream medical field and in consequence, into the industrial one. Industry 4.0 presents a wide, flexible range of challenges and opportunities for the well-being of workers; stress has become one such challenge. First, in the technological approach, the most successful industrial diagnosis projects tend to be custom-designed. This occurs due to the management of variables in an algorithm environment, which means that if stress diagnosis methods are not emphatically designed for a specific issue, they could lack the reliability for a company’s implementation. Second, the physicians' approach. This one holds the most effective reliability in its more traditional form, but, in respect to the formats of evaluation, it is more convenient as a support tool due to its many chances of bias. As a result, it would be prudent to implement a multi-phase analysis within a company, combining the best features of both approaches and using the indexes as a supplement to a technologically based diagnosis. This way, the continuity and practicality of technological diagnosis is maximized, while at the same time, you can muffle environmental bias with evaluation forms, preventing even coming at risk such that a health professional is needed.

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