2023 IEEE Symposium Series on Computational Intelligence (SSCI)
Mexico City, Mexico. December 5-8, 2023

Integration of Structural Equation Models and Bayesian Networks for Cognitive Load Modeling

Olha Shaposhnyk and Svetlana Yanushkevich
Biometric Technologies Laboratory, Schulich School of Engineering
University of Calgary, Canada
olha.shaposhnyk1@ucalgary.ca, syanshk@ucalgary.ca

***Abstract*—This study offers a causal probabilistic modeling for inferring the relationship between humans' cognitive load, the physiological signal predictors of such load, and personality traits. We selected a subset of such signals (heart rate, intervals between successive heartbeats, galvanic skin response, and temperature) from the CogLoad dataset using wearable devices. Structural Equation Modeling techniques were employed to select the predictors to identify the level of cognitive load, for which the ground truth was assessed using subjective tests such as HEXACO that determine the personality traits of the human subjects. Bayesian networks were deployed to investigate the causal relationship and model the inference scenarios. The proposed model is intended to contribute to developing a Computational Intelligence tool for monitoring social health in scenarios of future potential crises such as pandemics and mass migration.**

***Index Terms*—cognitive load, physiological response, personality traits, emotions, machine reasoning, mental workload, probabilistic inference, Bayesian network, structural equation modelling**

I. Introduction

Assessing a human's cognitive load holds significant importance in detecting overload and stress that have physical and mental health implications [1]. Prolonged or chronic stress has been associated with adverse outcomes, including cardiovascular diseases, immune disorders, and mental health disorders [2]. Early identification of stress allows to implement appropriate strategies to manage and alleviate stress, promoting overall well-being. In professions characterized by high-pressure environments, such as first responders, monitoring stress levels can help prevent accidents, optimize performance, and ensure the safety of individuals and those around them [3], [4]. Stress detection also proves valuable in healthcare settings by identifying patients who may be susceptible to stress-related complications, facilitating timely intervention and tailored support.

Investigating the impact of emotional and cognitive load, including stress and burnout, poses challenges due to the subjective nature of these phenomena and the lack of a universally defined "ground truth". Stress, in particular, varies among individuals, with different stimuli triggering stress responses in some individuals but not others. Therefore, when assessing cognitive and emotional load that can lead to stress, it is crucial to consider individual personality traits and other characteristics.

This paper is structured as follows: In Section II, we present a survey of the most important related works. Section III outlines the approach and methodology adopted for this study. In Section IV, we describe the experimental settings and present the results obtained. Finally, Section V concludes the paper.

II. Related Works

In [5], an AI-driven Driver Assistance System for stress detection in car drivers was introduced, using wearable sensors to capture physiological signals like ECG, EMG, Galvanic Skin Responds, and beat-to-beat intervals. However, there was no indication of the system's adaptability to a range of driving conditions, including frequency of real-life driving, and years of vehicle usage. Paper [6] employed EEG signals for remote mental workload identification. It integrated spatial and time–frequency features through a hybrid deep learning model, enhancing classification accuracy. However, these approaches solely rely on biological signals to assess workload, disregarding individual characteristics such as age, gender, occupation type, and other relevant factors.

The issue of mental fatigue and its connection to cognitive performance is addressed [7], using Heart Rate Variability data and machine learning to detect and predict fatigue. However, the study's participants consisted solely of university students, with an average age of 22, which limits the applicability of these results to the broader population.

In [8], an intelligent stress monitoring tool was proposed that combines deep learning to detect physiological stress (one of three states) and then uses the Bayesian network (BN) to explore the causal relationship between the physiological indicators. The study was limited to the data from WESAD set [9], which did not include the assessment of personality traits using psychological or other subjective tests. The ground truth was defined using the setup conditions such as running, relaxing or watching horror movies.

In [10], the authors used BNs to analyze the influence of working conditions on occupational accidents, focusing on the interconnectedness between physical and psychological symptoms and their association with occupational accidents. BNs and their extensions were applied for risk assessment in biometric-enabled systems [11] and analysis of physiological signals [12].

The work [13] using CogLoad dataset suggested applying machine learning approaches to assess cognitive load using physiological measurements. The research explored the potential of physiological "biomarkers" recorded by wearable

978-0-7381-4408-5/23/$31.00 ©2023 IEEE

Fig. 1. Causal Modeling Workflow that involves expert consultation, correlation analysis, SEM validation, and Bayesian network construction.

devices for assessing high cognitive load in real-time scenarios, using probabilistic causal graphs.

Several studies conducted an ensemble-type analysis, combining outcomes from various models such as Structural Equation Modeling (SEM) and BN. For example, daily health indicators were modeled in [14] using the scheme:

$$\texttt{Data} \longrightarrow \texttt{BN} \longrightarrow \texttt{SEM}$$

In this approach, an initial exploratory BN is performed on the data, followed by the identification of the most significant nodes in the BN, which are then incorporated into an SEM. A "what-if scenario" of interest was subsequently built.

The same scheme was used in [16]. The model was exploited to study factors contributing to low back pain-related disability. Specifically, the structural paths from the BN were employed in SEM analysis to estimate the parameters of interest. A similar approach was employed in [17] for risk analysis in project management.

A hybrid model of SEM and BN, was utilized in [15] to study the social problem of career satisfaction, represented by the linkage:

$$\texttt{Data} \longrightarrow \texttt{SEM} \longleftrightarrow \texttt{BN} \longleftarrow \texttt{Data}$$

In our approach, we use SEM to comprehensively capture the complex links between physiological signals, cognitive load, and individual personality traits. This SEM framework forms the basis for constructing a BN that integrates these variables, going beyond superficial connections to unveil deeper interdependencies.

$$\texttt{Data} \longrightarrow \texttt{SEM} \longrightarrow \texttt{BN}$$

Unlike previous studies, we focus on creating a causal framework that uncovers the profound relationships among cognitive load, physiological indicators, and unique personality traits. The Cogload dataset was chosen due to its diverse cohort, characterized by variations in age and gender. The dataset offers an extensive array of personality trait information, facilitating an in-depth exploration of the nexus between physiological reactions to workload and the influencing personality attributes. The participants' also completed the post-task surveys, wherein they articulate their experiential load across diverse dimensions. However, the dataset predominantly comprises tasks of a similar nature, which has guided the study's focus exclusively toward cognitive load considerations.

III. Approach and Methodology

In this study, we aim to model a causal relationship between the physiological indicators of cognitive workload, such as performing complex mental tasks, and the participants' personality traits. To achieve this objective, we leverage SEM to capture the relationship between physiological signals, level of cognitive load, and personality traits. We then use the SEM to construct a BN that integrates these variables. The BN allows us to capture the dependencies and conditional probabilities between variables, to examine how the physiological indicators and personality traits contribute to the prediction of cognitive load levels, and to perform inference of potential extreme-case scenarios such as overload. This methodological paradigm offers an avenue for advancing the understanding of the underlying mechanisms impacting cognitive and phisiological processes.

Our approach is illustrated in Figure 1. The experimental design includes data selection and preparation, choosing the methodology to create and verify the graph models, and utilizing the graph models to perform inference. We built the general structure of the network, including demographics (age and sex) and a comprehensive set of personality traits, including honesty, extraversion, experience, emotionality, agreeableness, and conscientiousness. These personality traits were derived from a psychological assessment tool called the HEXACO personality inventory [18]. Physiological signals obtained from wearable wristbands are also incorporated into the network's structure.

We built an entire BN capturing multiple variables, which can be accessed GitHub repository link: https://github.com/ExcellentDarkTea/BN-SEM-article. For illustration purposes and due to space constraints, we provide a sub-network that captures the causal relationship between personality traits and demographics.

A. Data selection

In this investigation, we used the CogLoad dataset [20], which includes physiological signals and personality traits data. Participants completed a HEXACO Personality questionnaire [18], measuring six personality dimensions: Honesty-Humility, Emotionality, Extraversion, Agreeableness, Conscientiousness, and Openness to Experience. This dataset provided a comprehensive view of participants' personality traits with 30 variables derived from the assessment.

Physiological data from the signal measured by the wearable sensor Microsoft Band 2 were recorded: Galvanic Skin Response (GSR), Temperature (Temp), Intervals Between

Successive Heartbeats (RR) and Heart rate (HR). Demographic information such as age, gender, and education level have been included in the dataset as well.

We perform the data processing as follows. First, we removed outliers and invalid data points, including segments affected by sensor breakdowns. To further enhance data accuracy, we applied a Savitzky-Golay filter [19] to smoothen the data and eliminate noise. Next, we performed data normalization and standardization to bring the data into a consistent format and scale. Features were then extracted using an 11-second rolling window with a 1-second offset. For each of the four physiological measures (HR, RR, GSR, and temperature), statistical characteristics such as $Mean$, Min, Max, $Range$, 1st Quantile ($Q25$), 2nd Quantile ($Q50$), and 3rd Quantile ($Q75$) were computed.

B. Probabilistic graph models

In this work, we will deploy probabilistic graph models that include SEM [21] and BNs [22].

SEM is a statistical technique used to examine causal relationships among variables. Using statistical software and goodness-of-fit measures, SEM provides a quantitative framework for understanding the complex interconnections within a system.

BNs allow to represent a set of variables and their conditional dependencies via a directed acyclic graph, thus capturing the joint distribution between the variables. It is used to answer probabilistic queries about variables, that is, to perform inference. For instance, it allows to update knowledge of the state of a subset of variables when other variables are observed by computing the posterior distribution of variables given evidence. This is implemented by applying Bayes' theorem. Thus, BNs allow reason and support decision-making under uncertainty. They can handle both discrete and continuous variables represented via their distributions.

To establish the structure of our causal network, we undertook several steps:

- Expert Consultation: We consulted experts in the field to gather their insights and opinions regarding the proposed network configuration.
- Correlation Analysis: We thoroughly analyzed the correlation matrix to identify and examine the relationships between physiological signals and personality traits. This allowed us to identify significant associations and discern patterns within the dataset.
- SEM Validation: We employed SEM to validate the proposed structure of the causal network, to test the fit of our model to the data.
- Expert Review and Refinement: To ensure the accuracy and reliability of our results, we sought further input from domain experts to refine the structure of the causal network accordingly.
- BN Construction: Finally, we constructed the causal network, BN, a probabilistic graphical model that incorporates both observed data and prior knowledge, enabling us to represent and analyze the complex relationships between physiological features and personality traits.

Correlation quantifies the relationship between two variables, indicating how changes in one relate to changes in another. Correlation coefficients between 0.3 and 0.5 (or -0.3 to -0.5) signify moderate correlations, suggesting a noticeable but not excessively strong linear connection. Coefficients exceeding 0.5 (or falling below -0.5) indicate strong correlations, implying a robust linear relationship where changes in one closely match changes in the other.

There is a growing body of evidence supporting the assumption that psychological traits have a significant impact on cognitive workload and stress levels [23]. These findings suggest that understanding the relationship between psychological traits and workload is crucial for designing an effective decision-support system for first respondents.

To analyze this relationship, the dataset was divided into two subsets: one for cognitive load and another for rest data. Our analysis observed correlations between specific personality traits and indicators of stress signals or rest. Specifically, we found that traits such as fairness, dependence, sociability, liveliness, gentleness, prudence, and honesty exhibited correlations with stress signals. On the other hand, traits like sincerity, fairness, dependence, liveliness, flexibility, patience, diligence, and openness showed correlations with the rest data.

Note that while these correlations do not mean causation, they provide foundational information about potential relationships between variables.

Generally, the correlation values ranged between 0.3 and 0.5 (-0.5 and -0.3). These moderate correlation strengths suggest that changes in one variable are moderately associated with changes in the other.

Table I presents the part of the correlation analysis results showcasing the relationships between the variables under investigation. It highlights the pairwise correlations between personality traits, demographic factors, and physiological markers such as RR. We have highlighted values that show these moderate correlation strengths. We will use the personality traits that are significantly correlated with physiological signals as inputs for building SEM and BN.

TABLE I
CORRELATION ANALYSIS BETWEEN PERSONALITY TRAITS AND RR VALUE

Personality traits	$Mean$	Min	Max	$Q25$	$Q50$	$Q75$
fairness	**0.464**	**0.439**	**0.478**	**0.449**	**0.459**	**0.469**
dependence	**0.313**	0.293	**0.327**	**0.301**	**0.309**	**0.318**
gentleness	**0.320**	0.298	**0.334**	**0.307**	**0.317**	**0.326**
patience	0.131	0.127	0.132	0.129	0.130	0.131
prudence	-0.284	-0.260	**-0.301**	-0.270	-0.281	-0.292

Note that the modest strength of these correlations and the sample size limitations should be considered when interpreting the results.

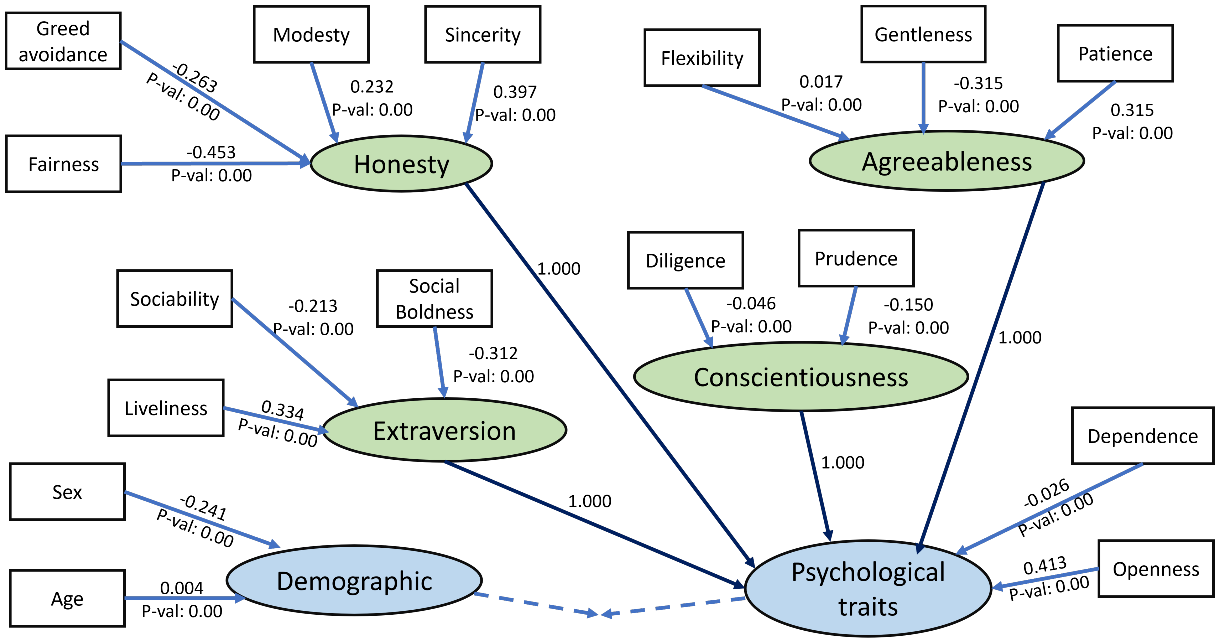

Fig. 2. SEM model depicts the causal relationship between personality traits: the upper number is a Regression Coefficient between variables, and the lower number p-val is the Chi-Square test significance (p-value needs to be below 0.05)

C. Building SEM

To build the SEM model, we define the latent variables, observed variables, and the hypothesized relationships between them.

SEM analysis includes computing standardized coefficients representing the strength and direction of the relationship between variables. Positive coefficients indicate a positive relationship, while negative coefficients indicate a negative relationship. The magnitude of the coefficient indicates the strength of the relationship. P-values associated with the coefficients help determine the statistical significance of the relationships. Generally, p-values below a certain threshold (e.g., 0.05) are considered statistically significant, indicating that the relationship is unlikely to have occurred by chance.

In cases where standard errors and p-values are absent for latent variables, an estimated relationship of 1.00 between those variables is indicated.

Multiple versions of the SEM were constructed in this study. All variables observed in the graph prototype were included in the initial iteration. Subsequently, the SEM results were analyzed to identify nodes with non-significant connections (p-value greater than 0.05), which were removed, and the graph was reorganized to optimize its structure.

Our final SEM was divided into three parts to capture the relationships within our research domain comprehensively. In the first part (Figure 2), we examined the interconnections between personality traits, as determined by the HEXACO survey, and demographic factors. This portion of the model illustrates how an individual's personality, age, and sex can influence their response to workload demands.

We also created SEM for the relationships between various bio-signals, such as GSR, temperature, RR, and HR, in detecting and quantifying workload levels. Those results are presented on GitHub and not illustrated here due to space constraints.

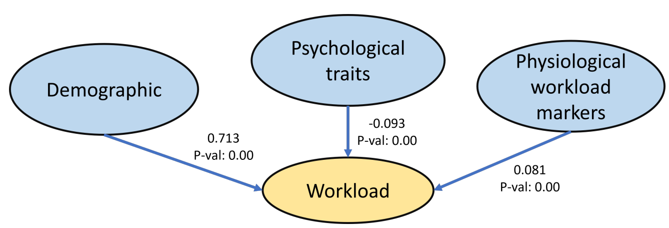

Fig. 3. Macro-level of final SEM mode: above value is Regression Coefficients between variables, below p-val is the Chi-Square test significance (p-value needs to be below 0.05)

The macro-level of our SEM (Figure 3) combines the personality traits and bio-signal data, showcasing the interconnectedness between individual characteristics and physiological responses to workload. By considering both personal attributes and physiological responses, we obtain a comprehensive understanding of how individual traits and bio-signals collectively influence the experience and manifestation of workload.

D. Designing BN

To construct a BN based on the causal network, it is necessary to assign conditional probability tables (CPTs) to each variable. These CPTs capture data distributions and provide valuable information for the BN. We employed the PyAgrum library in Python to create the BN.

Our complete BN consists of a total of 46 nodes, representing various variables of interest.

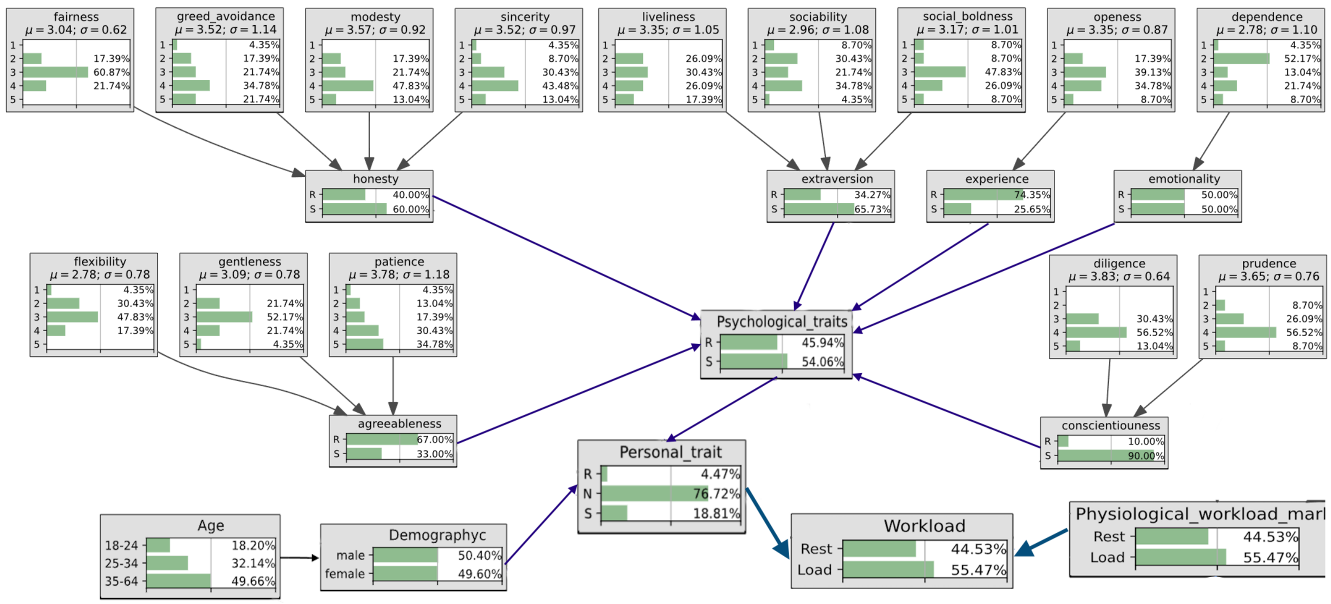

Fig. 4. Part of the BN, which models the interplay between Personality traits and Demographics created using PyAgrum.

Below, we illustrate a fragment of the BN that accounts for personality traits and demographics. To create the CPTs, we categorized age into three distinct groups: 18-24 representing early adulthood, 25-34 representing middle adulthood; and 35-64, representing old adulthood. To assign CPTs to the Demographic and Age nodes, we utilized open data pertaining to a country's population [24].

Subsequently, we calculated statistics for each node about the personality traits derived from the HEXACO model. This involved analyzing the distribution of scores ranging from 1 to 5 for each personality trait facet. By examining these distributions, we gained insights into the frequency with which individuals exhibited specific scores for each facet.

Building upon the correlation matrix obtained in step two, we populated the dimensions of the BN. This process involved assessing the impact of each facet on the cognitive load or rest state. For instance, consider the dimension "Agreeableness" with its three facets: "flexibility," "gentleness," and "patience." Upon analyzing the correlations, we found that "flexibility" and "gentleness" were associated with Rest, while "patience" showed a correlation with stress. Consequently, we inferred that two of the three facets influenced the rest state, while only one impacted the workload (stress) state. This indicates that individuals with these specific facets were likely to be affected by Rest at a rate of 67% and by the cognitive load at a rate of 33%.

As a result, three distinct classes of person traits were identified based on demographic and psychological information: Stressed, which means a state under a workload (S), a state of Rest, or no-load (R), and Neutral (N).

In the context of our study, reminiscent of the scenario involving a converging connection [22], we opted to combine physiological workload markers and personal traits during the final analysis phase. For the purpose of this integration, we utilize the OR and NOR operators as follows: when the physiological workload markers indicate a state of rest, we activate the OR operator to amalgamate this data with personal traits; we used the NOR operator when the markers indicate the absence of rest.

The final graph for the assessment of workload probabilities predicated on an individual's distinct assemblage of physiological markers and personality attributes is displayed in Figure 4.

IV. Examples of Inference on the BN

In this section, we provide three examples of such inferences on the BN as follows:

Example 1. Consider an individual with a Personality trait being Neutral (N), and the data is available from wearable sensors on that subject. The Bayesian inference estimates the likelihood of the person performing cognitive tasks as 89.63%, as shown in Table II, line 1.

Example 2. Suppose we have a 20-years old male firefighter, and we have access to data from two sensors: temperature and GSR. By employing Bayesian inference, we can estimate the likelihood of the individual experiencing a cognitive workload. Based on the analysis conducted on the BN, the estimated likelihood of such workload is 70.04%, as shown in Table II, line 2.

*Example 3.*Consider a 40-year-old woman with extensive work experience. According to the psychological test, she falls under the R category. While the HR sensor detects a workload, the other sensors indicate a state of rest. We can estimate the likelihood of the subject performing a cognitive task. Based on the analysis conducted on the BN, the estimated likelihood of the state of such workload is determined to be 36.16%, as shown in Table II, line 3.

TABLE II
PROBABILITY OF A COGNITIVE WORKLOAD GIVEN DEMOGRAPHIC DATA

Workload	Yes, %	No, %
1. Neutral type subject	89.63	10.63
2. A 20-year old man under load	70.04	29.96
3. A 40-years woman at rest	36.16	63.84

V. CONCLUSION

The reported results suggest the following conclusions:

- The causal models capture the relationship between the level of cognitive load, the physiological signal that act as a predictor of such load, and the personality traits of the human subjects.
- The developed reasoning model acts as a decision support component, integrating real-time physiological data, personality traits, and demographic information.
- The created models allow for probabilistic inference and assessing the posterior probability of certain risks and events.

This work contributes to the ultimate goal of creating a Computational Intelligence (CI) tool for assessing a human's affective state under a cognitive load. Such CI tool's function is to detect abnormal levels of stress, such as burnout, and to alert the system that monitors the state of human subjects, such as first responders, firefighters, rescue operators and combatants. This information can further guide the rescue task assignment, considering responders' current cognitive capacity, thereby maximizing their effectiveness while minimizing the risk of errors caused by cognitive overload.

The research makes a significant contribution by integrating personality traits with physiological data to assess cognitive load accurately. It employs probabilistic graphical models (SEM and BNs) and emphasizes data quality through detailed preprocessing. This holistic approach finds practical application in high-stress environments like first responders, backed by expert involvement and transparency in model development, enhancing its real-world relevance.

ACKNOWLEDGMENT

We acknowledge the partial support of the Government of Canada's New Frontiers in Research Fund, NFRFR-2021-00277.We also acknowledge suggestions and discussions with Dr Ie.Nastenko, and PhD students V. Babenko and M. Chernykh.

REFERENCES

[1] G.P. Chrousos, Stress and Disorders of the Stress System, *Nature Reviews Endocrinology*, vol.5, no.7, pp.374–381, 2009.

[2] A. Steptoe and M. Kivimäki, Stress and Cardiovascular Disease: an Update on Current Knowledge, *Annual Review of Public Health*, vol.34, pp.337–354, 2013.

[3] T.D. Shanafelt, S. Boone, L. Tan, *et al.*, Burnout and Satisfaction With Work-Life Balance Among US Physicians Relative to the General US Population, *Arch Intern Med.*, vol.172, no.18, pp.1377–1385, 2012.

[4] E. Van der Ploeg and R. J. Kleber, Acute and Chronic Job Stressors Among Ambulance Personnel: Predictors of Health Symptoms, *Occupational and Environmental Medicine*, vol.60, pp. 40–46, 2003.

[5] A.I. Siam, S.A. Gamel and F.M. Talaat, Automatic stress detection in car drivers based on non-invasive physiological signals using machine learning techniques, *Neural Comput & Applic*, vol.35, pp.12891—12904, 2023.

[6] S. Shao, G. Han, T. Wang, *et al.*, EEG-Based Mental Workload Classification Method Based on Hybrid Deep Learning Model Under IoT, *IEEE Journal of Biomedical and Health Informatics*, pp.1–10, 2023.

[7] A. Matuz, D. Van der Linden, G. Darnai, *et al.*, Generalisable machine learning models trained on heart rate variability data to predict mental fatigue, *Sci Rep*, vol.12, p.20023, 2022.

[8] K. Lai, S.N. Yanushkevich and V. P. Shmerko, Intelligent Stress Monitoring Assistant for First Responders, *IEEE Access,* vol. 9, pp. 25314–25329, 2021.

[9] P. Schmidt, A. Reiss, R. Durichen, C. Marberger and K. Van Laerhoven, Introducing WESAD, a Multimodal Dataset for Wearable Stress and Affect Detection, *Proc. 20th ACM International Conference Multimodal Interaction*, pp. 400–408, 2018.

[10] S. García-Herrero, M.A. Mariscal, J. García-Rodríguez and D.O. Ritzel, Working conditions, psychological/physical symptoms and occupational accidents, Bayesian network models, *Safety Science*, vol.50, no.9, pp.1760–1774, 2012.

[11] S.C. Eastwood and S.N. Yanushkevich, Risk Assessment in Authentication Machines, In: Abielmona, R. (Eds.), *Recent Advances in Computational Intelligence in Defense and Security, Series*, vol. 621, Springer, pp 391–420, 2016.

[12] X.A. Fan, L.Z. Bi and Z.L. Chen, Using EEG to Detect Drivers' Emotion with Bayesian Networks, *Proc. IEEE International Conference on Machine Learning and Cybernetics*, vol. 3, pp. 1177–1181, 2010.

[13] O. Shaposhnyk, V. Babenko, M. Chernykh, S. Yanushkevich, and Ie. Nastenko, Inferring Cognitive Load Level from Physiological and Personality Traits, *Proc. IEEE Conf. Information and Digital Technologies (IDT 2023)*, Slovakia, pp. 233–241, 2023.

[14] R. S. Kenett, G. Manzi, C. Rapaport, and S. Salini, Integrated Analysis of Behavioural and Health COVID-19 Data Combining Bayesian Networks and Structural Equation Models, *Int. J. Environ. Res. Public Health*, 2022, vol. 19, issue 4859.

[15] W. Wipulanusat, K. Panuwatwanich, R. A. Stewart, J. Sunkpho, and P. Thamsatitdej, Achieving career satisfaction through fostering innovation: lessons from the engineering profession in the Australian public sector, *Engineering Management in Production and Services*, vol. 13, no. 4, pp. 7–21, 2021.

[16] B. X. W. Liewa, J. Hartvigsenb, M. Scutarid, and A. Kongsted, Data-driven network analysis identified subgroup-specific low back pain pathways: a cross-sectional GLA:D Back study, *J. Clinical Epidemiology*, vol.153, pp. 66–77, 2023.

[17] S. Gerassis, M.T.D. Albuquerque, J.F. Garcia, C. Boente, E. Giraldez, J. Taboada, and J.E. Martin, Understanding complex blasting operations: A structural equation model combining Bayesian networks and latent class clustering, *Reliability Engineering and System Safety*, vol. 188, pp. 195–204, 2019.

[18] K. Lee and M.C. Ashton, The HEXACO Personality Inventory - Revised, https://hexaco.org/hexaco-online

[19] S. Hargittai, Savitzky-Golay least-squares polynomial filters in ECG signal processing, Computers in Cardiology, pp. 763-766, 2005.

[20] M. Gjoreski, T. Kolenik, T. Knez, *et al.*, Datasets for Cognitive Load Inference Using Wearable Sensors and Psychological Traits, *Applied Sciences*, vol. 10, no. 11, pp. 3843, 2020.

[21] A.A. Igolkina and G. Meshcheryakov, Semopy: A Python package for structural equation modeling. Structural Equation Modeling, *A Multidisciplinary Journal*, vol.27, no.6, pp.952–963, 2020.

[22] N.Fenton and M. Neil, *Risk Assessment and Decision Analysis with Bayesian Network*, 2nd ed., CRC Press, Taylor & Francis Group, Boca Raton, FL, 2019.

[23] I. Pilch, Comparison of the Big Five and the HEXACO Models of Personality in the Prediction of Emotional Wellbeing: an Experience Sampling Study, *Trends in Psychol*, pp. 1-17, 2023.

[24] Government of Canada, Canada's population estimates: Age and sex 2022, Statistics Canada, https://www150.statcan.gc.ca/n1/daily-quotidien/220928/dq220928c-cansim-eng.htm