Heart Rate Variability Measurement to Assess Acute Work-Content-Related Stress of Workers in Industrial Manufacturing Environment—A Systematic Scoping Review

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***Abstract*—*Background:* Human workers are indispensable in the human–cyber-physical system in the forthcoming Industry 5.0. As inappropriate work content induces stress and harmful effects on human performance, engineering applications search for a physiological indicator for monitoring the well-being state of workers during work; thus, the work content can be modified accordingly. The primary aim of this study is to assess whether heart rate variability (HRV) can be a valid and reliable indicator of acute work-content-related stress (AWCRS) in real time during industrial work. Second, we aim to provide a broader scope of HRV usage as a stress indicator in this context. *Methods:* A search was conducted in Scopus, IEEE Xplore, PubMed, and Web of Science between 1 January 2000 and 1 June 2022. Eligible articles are analyzed regarding study design, population, assessment of AWCRS, and its association with HRV. *Results:* A total of 14 studies met the inclusion criteria. No randomized control trial (RCT) was conducted to assess the association between AWCRS and HRV. Five observational studies were performed. Both AWCRS and HRV were measured in nine further studies, but their associations were not analyzed. Results suggest that HRV does not fully reflect the AWCRS during work, and it is problematic to measure the effect of AWCRS on HRV in the real manufacturing environment. The evidence is insufficient for a reliable conclusion about the HRV diagnostic role as an indicator of human worker status. *Conclusion:* This review is valuable in the Operator 4.0 paradigm, calling for more trials to validate the use of HRV to measure AWCRS on human workers.**

***Index Terms*—Heart rate variability (HRV), human–cyber-physical system (H-CPS), Industry 5.0, Operator 4.0, stress, systematic literature review.**

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I. Introduction

INTEGRATING humans and cyber–physical systems (CPSs) in Industry 4.0 (I4.0) into human-CPSs (H-CPS) needs special regard [1] and requires the assessment of both human physiological and machine parameters. This study is conducted to collect the evidence and foundation of using heart rate variability (HRV) as an indicator for acute work-content-related stress (AWCRS) in an industrial manufacturing environment for further work content adjustment.

A. Background

Thanks to the connectivity of the Internet of Things (IoT), workers became part of an intelligent system [2], [3] and the H-CPS [4], [5], [6], [7], [8], [9]. Though I4.0 endorsed the automation of CPS [10], human workers are still indispensable in manufacturing industries [11]. The Operator 4.0 concept suggests developing a socially sustainable manufacturing workforce with the H-CPS [12]. Industry 5.0 (I5.0) was proposed by the European Union (EU) with human-centricity as one key objective [13]. In this emerging context, using HRV measurement to build physiological monitoring systems is promising, with many possible data-driven solutions developed [14], [15], [16].

Stress is considered emotional tension and discomfort with demanding circumstances [17]. According to World

Health Organization (WHO), work-related stress appears when workers face work demands that out-weight their abilities. The stress sources are divided into work content and work context [18], [19], which consequently affected work performance [20], [21], [22] and the occupational health and safety (OHS). Repeated exposure to stressful work content generates both acute and chronic stress, posing a detrimental effect on physical and mental health [23]. Considering the case of blue-collar workers, the stress influence of work content had a direct relation with physical symptoms [24], reducing cognitive ability and increasing the accident occurrence [25].

One objective, well-known indicator of stress is HRV, which has intrinsic mathematical chaotic characteristics and can reflect many physiological factors [26]. Stress recognition by assessing HRV is scientifically proven by neurobiological evidence [27]. With the attributes of noninvasive, safe, easy-to-use, and simple diagnostic tests, HRV measure can replace traditional cardiovascular diagnostic tools [28] to assess job-related cardiovascular stressors [29], and exhibit different induced effects by acute and chronic stress [30].

In a manufacturing environment, to avoid any long-term accumulation of occupational stress, any unfavorable work content should be adjusted timely with the early sign of AWCRS. Without a unified definition, the idea of AWCRS monitoring has been utilized many times in literature. It is the core concept for just-in-the-moment adaptive interventions (JITAI) [31], with the deployment of individual tracking devices to create a physiological signals monitoring system [32]. Sajno et al. [33] proposed an HRV monitoring procedure to detect the stress and tiredness level of workers; thus, safety cyber-intervention can be delivered.

B. Research Gap

However, as the technology is ready, the concern becomes whether HRV can be an indicator of AWCRS in an industrial production environment. Studies exploring this use of HRV have not yet been systematically reviewed. A systematic review by Järvelin-Pasanen et al. [34] explored the associations between occupational stress and HRV. Among ten studies identified up to 2017, only three focused specifically on manufacturing workers. Studies on HRV as an objective psychological stress measure have been systematically reviewed (2018) in [27]. The 37 studies identified were conducted in rather heterogeneous samples (including mainly healthy participants, white-collar and computer workers) and only a few studies focused specifically on industrial settings (e.g., shipyard workers). Overall, the authors did not draw firm conclusions regarding the association between AWCRS and HRV, and none of the studies assessed HRV as an instantaneous indicator of AWCRS. The studies in [35] concern the HRV measured by smart devices and wearables as an indicator for acute stress. However, they did not distinguish the effect of work content from other types of stressors. Several studies adopted HRV as a short-term response to acute mental stress in laboratory simulation with standardized tasks [36], [37], but these do not resemble the industrial environment. This knowledge gap leads to difficulties for researchers who aim to develop new data-driven solutions based on individual physiological parameters.

C. Objectives

This article explores the available evidence on HRV as an indicator of AWCRS to provide a basis for JITAI to optimize worker performance. Secondarily, it aims to provide a comprehensive conceptualization of the current development in the usage of HRV as an indicator of AWCRS in the industrial manufacturing context via a systematic review.

II. Materials and Methods

A. Search Strategy and Eligibility Criteria

A separate protocol for this study has been summarized in a previous publication [38]. Details of the search strategy and eligibility criteria can be found in the Supplementary Materials.

B. Study Selection

The records identified by the search were downloaded and handled in the Mendeley citation management software [39], and duplicates were removed. The study selection was carried out in two stages: 1) title and abstract screening and 2) full-text screening. Each stage was performed by two researchers (TT and MNH) independently. Any discrepancies that occurred were discussed among all the authors. A specifically designed Excel spreadsheet was developed and used to screen, select papers, and compile extracted data.

C. Data Extraction

Studies were categorized by the study types, with the highest priority for randomized controlled trials (RCTs). The data extraction was performed by one author (TT) and verified by three others (MNH, MP, and ZZ), which include the following.

1) *Study Characteristics:* Author, publication year, study type and purpose, population; work-content type and level, stress evaluation, HRV baseline, and measurement condition and duration.
2) Association of HRV with AWCRS.
3) *Evaluation Outcomes:* Conclusion and suggestion by the authors about using HRV to assess AWCRS.

Discrepancies between two independent reviewers were tackled by the same method in the previous screening phase.

III. Results

A. Search Result

The search was conducted in June 2022, resulting in a total of 101 papers. The number of duplicates removed was 30, 71 abstracts were reviewed, and 39 full-texts were checked. The initial agreement level between the two reviewers was 91% and 58% in two scanning phases, respectively. After each discussion, these rates increased to 100%. Finally, altogether 14 papers reporting 14 different studies were included in the analyses. The PRISMA-based flowchart of the selection process can be found in the Supplementary Materials.

B. Study Characteristics

Further details about characteristics of the included observational and experimental studies, their stress evaluation, HRV measurement, HRV outcome, and the discovered association of HRV with AWCRS can be found in the Supplementary Materials, along with the conclusion and suggestion regarding HRV usage as an AWCRS indicator.

1) Study Purpose: Primary purposes of adopting HRV measurement for assessing AWCRS varied differently.

1) Discovering the health effect of existing work-content factors on the workers [40], [41], [42].
2) Validating the AWCRS detection of a proposed tool or intervention for industrial usage [43], [44], [45], [46].
3) Exploring the effect of AWCRS to find an optimal work content level [47], [48], [49], [50], [51], [52], [53].

2) Study Type: Two main study types were reported: 1) observational and 2) experimental. All five observational studies [40], [41], [42], [43], [47] were cohort studies. The rest nine experimental studies [44], [45], [46], [48], [49], [50], [51], [52], [53] were Non-RCT. Sutarto et al. [46] and Mixter et al. [53] adopted controlled studies, but randomization was not evident from the description.

3) Study Population: The mean sample size was 434 (median 30 participants). Eight studies considered male and female participants, while four only examined males [44], [49], [51], [52], and two only females [46], [53]. The study population means age was reported in 11 out of 14 studies and ranged from 19.9 [50] to 42.17 years [49].

Observational studies gathered data from large populations from real manufacturing companies, ranging from 135 [40] to 3797 workers [43]. The participants in experimental studies ranged from ten [44], [51], [52] to 40 workers [46] and were true workers in [46], [49], and [51], or colleague students in [48], [50], and [52], and local people in [45] and [53].

4) Work Environment and Additional Stressors: Observational studies were conducted in real manufacturing environments; which involved additional stressors besides the work content, such as noise [40], noise and hazardous exposure [41], and temperature and humidity [47]. Experimental studies were performed in a laboratory environment (except for the study of Hsu et al. [49]); thus, tight control could be deployed upon other work environments factors, such as different ambient oxygen contents, different weights, and safety shoes [52], or fixed posture during the experiment [53].

5) Work-Content Type and Induced Stress: Observational studies considered a few work-content factors derived from the existing work environment and cannot be adjusted. Shift work was the most frequent factor, with a day or night shift [41] or different shift patterns [40]. The second frequent object was the general job demand and job control [42], [47]. Physical workloads were the least frequent object [42].

Experimental studies show a variety of work-content factors. The physical aspect was the most studied factor, such as physical efforts [48], lifting movements [52], and repetitive tasks [53]. The cognitive requirement aspect was the second most frequently mentioned factor with the intrinsic demand of the work [50] or different difficulties, [53]. Teleoperation task with robots and machines was the next frequent topic [44], [45], comparing the effectiveness of the proposed consoles.

The work-content types were physical workload [47], [48], [52], or mental workload [48], [53] or both [48]. It was ambiguous to compare the levels of work content in these studies, as they took the information from the perception of workers without a specific description of the jobs, and there was no common scale of the experimental designs.

6) Stress Evaluation: Separated evaluations were conducted to validate the stress status, with the most popular tool being questionnaires. Karasek job content questionnaire (JCQ) [54] was used most frequently [40], [42], and effort–reward imbalance (ERI) [55] was the second popular option [41], [42]. Some studies employed more than one tool [41], [42]. NASA task load index (NASA-TLX) was used for working with equipment [51], or with machines [50], or assessing cognitive task performance [56]. Other tools were Cohen Perceived Stress scale [41], visual scale [48], situation awareness rating technique (SART) [50], Borg CR-10 scale [53].

Stress was also evaluated based on physiological parameters, such as by comparing electrocardiography (ECG) recordings from resting and working periods [45], [47], [48], [49]. The same approach was used with heart rate, and respiration rate [52], electromyography (EMG) [50], [51]. Other physiological signals were employed scattered, such as O2 consumption and energy expenditure [47], end-tidal CO2 [50], respiration rate [52], blood pressure and blood sample [41], [43].

Another additional stressor, such as workplace noise and ambient oxygen content, was assessed with the Ising questionnaire [40] and the ventilation response [52], respectively. Self-designed parameters, e.g., the number of correct responses or answers [48], [53], task efficiency and danger indices [44], were used. Biological specimens (e.g., urine or saliva samples) were deployed to strengthen the assessment [41], [43], [53].

7) HRV Measurement Instruments: Several studies employed professional ECG machines [40], [41], [42], [43], [47], [50], [51], [52], [53], while others employed sensors, such as wristband ECG [46], or wearable, such as Polar S810 [48], Polar RS800CX [49], Samsung Gear S smart-watch [45] for the mobility demand of the experiments. There were no data accuracy complaints.

8) HRV Baseline Measurement Condition: All included studies used the state of not working as the baseline condition, such as during sitting still periods [46], [47], [48], [49], [53], or during sleeping [40], [41], [42], [43]. Other baseline conditions were training sessions [52] and short breaks during experiment [45], [50]. The baseline duration varied from 10 min [50] to 2 h [52]. Noticeably, there was no baseline condition representing the normal working status.

9) HRV Measurement Condition: With the studies adopted throughout-the-day measurement approach [40], [41], [42], [43], the HRV measurement lasted for the whole working day, or working shift. The rest studies measured HRV in a shorter duration, varying from 5 min [45], [52] up to the whole working period [47], [48], [50], [51], [53].

10) Data Length for Analysis: From the HRV data of the working period, only short intervals were taken for analysis. The shortest duration was 2.5 min [45] while the longest duration was 5.35 min [41].

11) Utilized HRV Parameters: The HRV parameters were categorized into time-domain and frequency-domain.

1) *Time-Domain:* HR (mean heart rate, beats/minute), RR (RR interval, seconds), coefficient of variance of RR intervals (CVRR), SDNN (standard deviation of RR intervals, milliseconds), SDNNi (square root of the mean squared difference of successive RR intervals, milliseconds), SDRR (standard deviation of the IBIs for all sinus beats), root mean square of successive differences (RMSSD), NN50 (the number of pairs of successive RR intervals that differ by more than 50 ms), pNN50 (the proportion of NN50 divided by the total number of RR intervals);
2) *Frequency-Domain:* LF (low-frequency, milliseconds), normalized low frequency (nLF), %LF (percentage of LF power represents the relative power in proportion to the total power), HF (high-frequency, milliseconds), normalized high frequency (nHF), %HF (percentage of HF power represent the relative power in proportion to the total power), LF/HF (LF/HF ratio), VLF (very-LF band).

Several studies chose to analyze only one parameter, such as RMSSD [41], [42], [43], CVRR [44], LF [46], and HF [50]. Other studies analyzed more than two parameters [40], [47], [49], [51], [53]. The study of Ghaleb et al. [52] considered the highest number of ten parameters: HR, RR, SDRR, RMSSD, NN50, pNN50, LF, HF, LF/HF, and VLF.

C. Association of HRV With AWCRS

In most studies, HRV is reduced in more stressful situations. It was confirmed by stress evaluation tools that with a higher workload or work demand, the perceived stress among the workers and operators increased.

With workers facing high-demand tasks and high strain [47], the HR was elevated, and shift workers had a higher mean HR than day workers [40]. A higher carrying load [47], or a higher task frequency [52], a higher elevation of holding handheld scanner [51] also led to higher HR. However, with a light scanner [51], the effect of different elevations became insignificant. During consecutive sessions of physical tasks in [53], HR decreased. The difficulty level of the cognitive task did not significantly affect HR value [53].

The RR interval decreased when workers in stress condition [45], with a heavier workload of working with light scanners in high elevation [51], or higher lifting frequency [52]. However, this result differed between the two study replications.

CVRR increased with the new control method in [44].

SDNN was higher with high carrying weight [47], laser scanner device [51], higher task frequency or requirement of more muscles to perform [48]. SDNN also decreased with increased force exertion level [48] and was associated with age increase [47].

SDRR showed different behavior with the type of safety shoes and within replications [52]. SDNNi was elevated with rotating night shifts [40].

RMSSD reduced in workers experienced faster changing night shift [43], and higher ERI ratio [43]. This association depended on other factors such as age [42]. RMSSD did not show a similar trend within two replication in the study of [52]. During the consecutive sessions of physical tasks, RMSSD was increased [53].

NN50 showed a discrepancy between two replications in the study of Ghableb et al. [52], and the proportion of NN50 divided by the total number of RR intervals, pNN50, were differentiated by the types of safety shoes in the first replication with a specific lifting frequency.

LF decreased when the operators experienced stress when performing their work without biofeedback training [46] or working with a three-dimensional (3-D) scanner at a high elevation level [51]. However, in the same study, LF was also decreased in operators working with a light 3-D scanner.

Increased working surface height decreased the nLF [49]. On the contrary, %LF increased with workers under high JCQ demand and working with rotating night shift [42].

HF decreased with a high level of attention demand [50] and a higher elevation level of handheld devices [51]. HF was more responsive to physical movements, as suggested in the same study. However, the reverse effect was observed with different laser scanners. HF increased during physical tasks but showed no association with cognitive difficulty levels [53].

nHF elevated with increased working surface height [49].

The LF/HF ratio was significantly lower within workers working on higher surfaces [49] or with a higher elevation of handheld device [51], or higher lifting frequency [52].

VLF was decreased value corresponding to higher lifting frequency [52]. Lower oxygen content resulted in decreased VLF value, but only with the frequency of one lift per minute.

D. Conclusions Drawn by the Authors of the Original Papers About the Usage of HRV to Assess AWCRS

In some circumstances, there were associations between HRV and AWCRS. With workplace noise and job strain, AWCRS from physical activity during work can be reflected by HRV [40]. HRV contributed to the proposed ALI to measure the stress-related wear and tear of the body [43]. AWCRS from the physical workload and walking speed in the sugar industry [47], or in lifting work [52], teleoperation between humans and machines [44], during equipment control [45], working at height [49], sustained monitoring work [50], work with a 3-D scanner [51] were also be reflected by HRV. The authors of these studies recommended HRV as a task performance measure and a feedback source to design the work.

On the other hand, the rest studies stated different suggestions. There was no association of HRV with AWCRS, or the effect on HRV was caused by multiple stressors and could be separated to make any clear statement. The association was unclear and only appeared in 35–44 years old workers [42]. The mental workload corresponded closely to task differences as indicated by HRV, only when the physical workload was negligible or consistent [48]. On the other hand, the cognitive task difficulties did not yield a significant effect [53]. The effect of biofeedback training on the cognitive performance of the operator could be a long-term effect than an immediate one [46]. No suggestion on HRV usage was given in [41] and [53]. More studies are needed to have a deeper understanding before using HRV as a stress indicator.

IV. Discussion and Conclusion

A. Research Findings

Notably, most of the included papers were search results from engineering-oriented research. Only one study, identified through a predefined set of keywords, was reported in PubMed, which reflects the immaturity of this concept, especially from the perspective of life science. Among the 14 included studies, no RCT was conducted to assess the association between HRV and AWCRS, and none reported a high level of valid evidence of HRV as an indicator of AWCRS. The study design in the included studies was not robust against bias, as some studies only adopted a partly randomization procedure [51], [53].

There was an association between HRV and AWCRS, as HRV was reduced in the more stressful situation in most studies. However, the baseline conditions did not consider the HRV and stress effect during the normal working condition. Using a questionnaire for stress validation did not fully reflect the situation, as it took place after the work was over. The effect of AWCRS on the physical and physiological behavior of workers was dependent on many variables, i.e., working age, gender, and smoking, which were not fully discovered. The specificity and the diagnostic value of HRV were not assessed; thus, no reliable threshold can be concluded to determine the stressful situation.

The use of HRV to manage AWCRS was not addressed in observational studies. In experimental studies in [45] and [46], HRV measurement was a part of the intervention. However, the transition effect of AWCRS into chronic stress was not considered, as the working period for validation in these studies was short. If there was any training for the workers, their HRV value might exhibit better behavior during work, while the work content was still unfavorable. The other studies only adopted HRV values to validate if the experimental condition was stressful, without providing any information about the use of HRV as an intervention for AWCRS management.

In addition, the study designs in the included studies did not represent a good model of JITAI based on HRV value, as not all work-content factors were modifiable in a real-time manner. In some situations, e.g., robot manipulation [44] or biofeedback training [46], actionable interventions were available. In other cases, e.g., work schedule, an intervention to switch from night to day shift was not feasible.

Last but not least, the accrued value of the population can not represent the general workforce, and the study result can not be scaled for mass implementation. The studies were conducted in different work environments, and work-content stressors were not comparable, which reduced the generalizability of the results. The participants came from different fields, and their daily life status with existing chronic stress was not considered. Experiment sensitivity was not a concern within any of the included studies.

B. Conclusion

Integrating human physiological parameters into an H-CPS was considered an I5.0 development [1], [12], [57]. Stress is the most frequent measure that comes to mind, and HRV was one of its popular indicators. However, this review revealed that research on AWCRS in the industrial environment is still developing, mainly from an engineering perspective. Upon this aspect, we call for more elaboration and distinction of AWCRS from the typical stress types. Though in most studies, stressful situations were associated with reduced HRV, none of them were adequately designed to provide a sound scientific conclusion, nor did they successfully confirm the relationship between AWCRS and HRV. As HRV strongly depends on too many factors (e.g., work context, individual physical and mental status), its real-time usage for stress monitoring can be problematic. Based on the available evidence, a firm conclusion cannot be drawn whether HRV is a candidate indicator of AWCRS in an industrial manufacturing environment that deserves further investigation and validation work. Researchers can either develop a well-isolated simulation with predefined settings to discover the association and interpolate the result with relevant constraints during real-time monitoring, or utilize HRV along with other additional metrics within a strictly controlled environment. Future research should study the effect of work-content factors separately before combining them. A good example can be the study in [58] indicated that the impulsive sound could elevate the workload.

Though HRV-based intervention can reduce the AWCRS [45], [46], there was no validated evidence that supports the implementation of JITAI with real-time HRV monitoring. Though the robot manipulation was more precise with HRV feedback [45], the study design was insufficient to separate the effect from other factors, e.g., boredom or fixed posture. The JITAI approach with HRV as an AWCRS indicator needs more development before any industrial application. This approach can also take advantage of physiological sensors as introduced in [59], as an experiment type of study to perform ecological momentary assessment (EMA) on happiness, considering acute stress is a temporary status. The authors suggested continuously monitored HRV and a random assessment with a validated measure from another physiological parameter. Other biological specimens can be collected periodically to strengthen the assessed results. In addition, the association of HRV with the acute stress condition should be measured beforehand, such as the HRV can be sampled from the normal working condition as a reference, not only from the resting period. The effect of emotional variables should be studied, as HRV can adequately assess negative emotions [60].

Once the association between AWCRS and HRV was thoroughly studied, JITAI could be applied to improve human worker performance. This adoption aligned with the vision of Operator 4.0, and yields long-term benefits for the workforce and society in the forthcoming Industry 5.0 and Society 5.0 [61]. We urge more experiments, RCTs, and clinical trials to adopt a proper design and validate this approach before any commercialized platform can be built for real-time monitoring of HRV to manage AWCRS.

C. Author Contribution

János Abonyi, Levente Kovács, Márta Péntek, László Gulácsi, Zsombor Zrubka, György Eigner, and Tamás Ruppert shaped the research questions and search strategy. Tuan-Anh Tran, Tamás Ruppert, György Eigner, Márta Péntek, and Zsombor Zrubka developed the search terms and suitable databases. János Abonyi, Tamás Ruppert, and György Eigner provided advice from an engineering perspective, while Márta Péntek, Zsombor Zrubka, and László Gulácsi contributed to the social and psychological aspects. Tuan-Anh Tran wrote the first draft. All authors resolved the discrepancy in each stage and approved the final draft.

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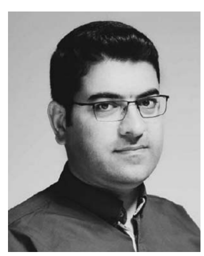

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