Smart Measurement of Human Factors and Productivity in Industrial Contexts

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Abstract. The integration of Artificial Intelligence (AI) and integrated sensors have enabled the measurement and improvement of worker and system performance across different industries. Despite these advances, Human factors (HF) remain underrepresented in management and engineering research literature, often relegated to occupational safety and human resources. This study conducts a systematic review of 39 empirical case studies over the past 14 years analyzing the impact of HF on industrial task performance using automatic measurement technologies. Findings indicate that research predominantly focuses on mental workload (51%), situational awareness (26%), and postural impact (21%), while the least explored constructs are physical fatigue (10%) and stress (8%). Since 87% of studies are laboratory-based, key challenges in industrial implementation remain unaddressed such as system interoperability, technological development, and worker acceptance. The study highlights the potential of HF measurement to improve productivity and workers' well-being through adaptive and augmentation systems, emphasizing the need for further real-world applications.

Keywords: Human Factors, Performance, Artificial Intelligence.

In recent years, the integration of Artificial Intelligence (AI) technologies and integrated sensors have allowed us to measure and improve performance in productive contexts [1]. These technologies are capable of measuring both worker performance and various key performance indicators (KPIs), enabling a learning cycle that adapts working conditions to improve system productivity [2]. For instance, in industries such as construction, allowing monitoring and quality control of the processes, as well as improvements in occupational safety and health (OSH) [3] or industries like agriculture where AI-enriched monitoring systems can track and predict crop growth [4]. Therefore, technological development provides promising evidence that an objective and continuous measurement of productive activities offers an opportunity to create systems capable of adapting and improving productivity in industrial environments.

Parallel to this technological development, there is a whole research area dedicated to ergonomics, also known as human factors (HF). This area focuses on improving human performance and well-being and has also leveraged sensor technologies and AI [5]. Advances in these technologies have significantly expanded the ability of measuring HF in real-time and non-invasively, enabling monitoring of parameters such as cardiac, respiratory, brain and muscle activity, among others [6], thus obtaining objective indicators regarding an individual's psychological, cognitive and physical state.

However, although technological developments have made it possible to measure both productive performance and HF, these latter have not been widely integrated into the management and engineering research literature. [7], not into the industry 4.0 literature. [8]. Scholars have stated that the overlook of HF in this area of knowledge is due to their being mostly addressed as an element of OSH or relegated to the realm of human resources [9]. Despite the increased integration over the years [10], the connection between these areas remains insufficient.

This fragmented view ignores the interdependent nature of operational factors and HF, and their combined effects on productivity limits the opportunities in the engineering and management research literature. It is crucial to note that workers operating under appropriate ergonomics design and cognitive-physical load perform with greater accuracy [11], lower error rate [12] and more efficient response to complex situations [13]. For instance, monitoring mental workload and situation awareness not only enables the identification of early signs of fatigue or overload, but also prevents potential operational stops, accidents [14] or high turnover [15]. While studies have started to integrate HF into productivity research [16], most of these studies are theoretical proposals, highlighting the need to assess real-world applications.

To address this gap in the literature, the present article aims to develop a review of empirical case studies that measure the effect of HF on task performance in industrial contexts using automatic measurement tools and AI. 39 publications addressing the topic from 2011 to the present were identified. Using the PRISMA model and performing a deductive analysis, adapting the theoretical model of HF integration in operations proposed by Neumann [17], [18].

Among the studies found, 26% focus on the construction industry, 18% focus on manufacturing and 16% focus on the medical field (mainly surgeries) with 16%. The prevalence of these industries could be explained by the high importance of OSH, as well as being areas where the human element plays a key role in the system´s productivity.

However, 87% of the studies are cross-sectional and laboratory-based, revealing significant gaps in industrial implementation. The main challenges include interoperability between systems, technological development, and worker acceptance. These limitations present opportunities to explore augmentation systems to enhance workers' capabilities, particularly in industries where human-AI collaboration is becoming increasingly critical.

Regarding the HF constructs assessed, there is a predominance of studies evaluating mental workload (51%), followed by situational awareness (26%) and postural impact (21%). The least explored constructs among the identified ones are physical fatigue (10%) and stress (8%). This distribution reflects the growing importance of cognitive factors in modern productive environments, especially with the integration of AI and automation.

The high interest in mental workload compared to other HF could be due to; (1) The impact that high levels of workload have on the number of errors made during information processing [19]; (2) development of non-invasive technologies capable of measuring mental workload, though cardiac, cerebral and ocular activity [20]; (3) sensitivity to task complexity [21] and (4) effect of mental workload on other HF constructs.

Among the measurement methods, the use of eye trackers stands out as the primary measurement tool (64%), followed by ECG (15%) and EEG (13%). Additionally, the integration of multimodal sensors and machine learning techniques allows the real-time analysis of the workers' physical and cognitive states, aiding in the implementation of preventive interventions in the future.

The results of this study contribute both theoretically and practically. Theoretically it was possible to verify the use of HF principles in the design of real production systems, highlighting the existing gap in the HF studies and their measurement methods. On the practical side, the potential of HF measurement to improve the productivity of production systems and the well-being of workers through adaptive and augmentation systems.

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