A methodology to select wearable devices for Industry 5.0 applications

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***Abstract*—The adoption of wearable devices is crucial in Industry 5.0 applications, but the devices' selection is cumbersome for practitioners and researchers due to the wide availability of models in the market. This work proposes a methodology based on the Analytic Hierarchy Process method to support the wearable devices selection in Industry 5.0 applications. The methodology helps in identifying the most suitable devices starting from the application requirements and devices' features analysis. We tested the methodology in a real industrial setting (human fatigue detection), successfully identifying the two most suitable wearable devices among a list of 110 alternatives.**

***Index Terms*—Industry 5.0, Human Digital Twin, Wearable Devices, Operator 4.0.**

I. Introduction

Digital representation of production systems become increasingly relevant in the last decade. There are countless examples of machinery and process monitoring solutions, including Digital Twins (DTs) [1], [2], to monitor machines, processes and factories. However, the continuously evolving needs of the manufacturing end-users require also to represent humans in the digital world, including their intents, behaviours and conditions, realising a so called Human Digital Twin (HDT) [3]. The digital representation of workers enables monitoring their conditions, allowing for *(i)* identifying the activities they are carrying out, *(ii)* simulating their behaviour for optimising production processes, *(iii)* improving the interaction with factory entities, including robots and Automated Guided Vehicles (AGVs), and *(iv)* improving their well-being [3]. In the monitoring context, wearable devices (also referred to as wearables) play a fundamental role [4] [5]thanks to the raising of advanced, precise, and low-cost sensors, which enable the collection and processing of human-related data to support analytics in a variety of applications [6].

Wearables are a category of electronic devices that can be worn as accessories, embedded in clothing, or even implanted in humans' body. Wearables are crucial to enable the Industry 5.0 (I5.0) paradigm [7], which revolves around the concepts of HDTs and Human-Cyber-Physical System to facilitate the human-machine cooperation [8]. Different types of wearables exist, including smartwatches, fitness trackers, smart clothing, smart glasses. and their usage in manufacturing production systems enables: *(i)* tracking and monitoring operator performance, behaviours and conditions [9]; *(ii)* supporting operator activities through innovative interfaces and support systems [10]. For example, physiological data from wearables support the estimation of other parameters (e.g., exertion and mental stress of workers) useful for adapting the behaviour of automation systems like collaborative robots [11].

Nowadays, the large market of wearables makes it difficult to identify those best suited for a specific industrial application. Researchers, industrial experts and companies face an increasing demand for technology selection methods and approaches, to support companies embracing I5.0 [12], but common practises and guidelines are still lacking.

This research presents a methodology to support wearable devices selection in the context of I5.0 applications. The paper is structured as follows: Section II highlights the relevance of wearable devices in I5.0; Section III provides a description of the proposed methodology and Section IV presents its application in a real-world environment for wearable devices selection to estimate the workers' fatigue exertion; Section V gives an overview of the next steps and future developments.

II. State of the art

Wearables available in the market collect data on workers' condition and behaviour, e.g., blood pressure, Heart Rate (HR) and sounds, pulse, perspiration/sweat, temperature, and a variety of metrics derived from motion and/or location measurements (like the energy consumption). Wearables onboard also environmental sensors to measure workplace-related metrics, like air quality, atmosphere pressure, noise, radiation, humidity, temperature. Modern wearables support wireless communication via a variety of technologies, including Wi-Fi, ZigBee, Bluetooth Low Energy (BLE), UHF/HF RFIS and others.In industry, wearables enable 4 functions: monitoring, supporting, training, tracking [13]. **Monitoring** is achieved with fitness trackers, smart rings, glasses, etc., and it covers the monitoring/control of both workers' vital parameters, and workplace parameters. **Supporting** increases workers' physical capabilities (e.g., to minimise musculoskeletal risks) by employing exoskeletons, patches, and wearable robots. **Training** capabilities are mostly based on application of VR/AR solutions like smart glasses, displays, helmets [14]. **Tracking** function enables collision prevention to increase safety and manage accidents, which is one prominent and widely exploited application within I5.0 use-cases [15].

To the best of our knowledge, this is the first work proposing a methodology to select wearable devices for I5.0 applications. However, some relevant works related to this topic proposed systematic literature review of wearables for ergonomics applications [16], or decision support for choosing the best suited wearables for studies related to sedentary behaviour [17]. While these studies are useful for decision makers to get insights, a proper selection procedure is not developed and proposed. However, insights discussed in previous works are suitable for inclusion in our methodology, either for features identification or feature importance assessment.

Finally, if we extend the scope to other non-manufacturing domains (especially in the context of health monitoring), we find other works that could serve as benchmarks, e.g., consumer-oriented methodology for selecting wearables based on everyday use criteria, and functionality criteria [18].

III. A METHODOLOGY TO SELECT WEARABLE DEVICES FOR INDUSTRY 5.0 APPLICATIONS

The proposed methodology for selecting wearables suitable for I5.0 applications starts with the identification of available options available in the market, followed by a selection process from the defined set of alternatives. The strength of the methodology lies in its practicality and business-oriented approach, which is lacking in other works on the topic [16]. The selection process is composed by the following 4 steps.

1. Features definition: this step identifies the requirements of the chosen application, from which we can derive the wearables features to use as selection criteria. Example of requirements include the kind of data to collect, the communication protocols to support, the environment in which the wearables should be employed. In the proposed methodology, we consider two main types of features:

- Primary features: features required to meet the application requirements. The number of primary features should be kept as low as possible, and in any case lower than 10. This constraint is given by the adoption of Analytic Hierarchy Process (AHP) in step 3.
- Secondary features: nice-to-have features relevant to the selected application (e.g., battery charge cycles).

2. Device identification: the step deals with the creation of a *technological database* containing the list of possible

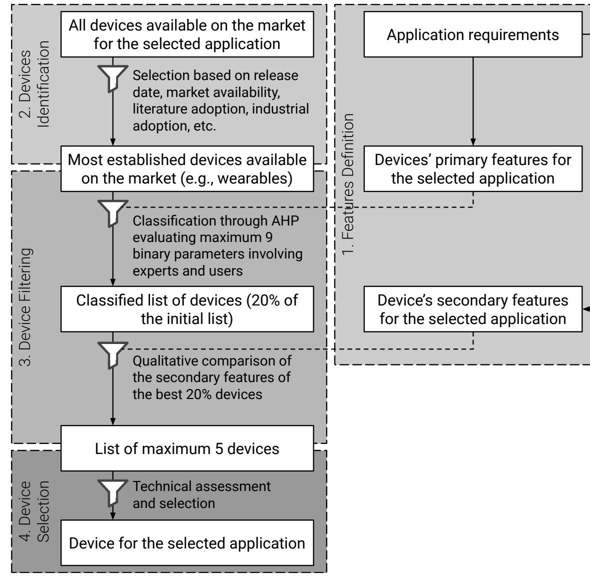

Fig. 1. The methodology for wearable device selection for I5.0 applications.

alternatives. It requires collecting devices' data sheets and/or technical specifications from the manufacturers; these data are used to assign values to both primary and secondary features, based on different scales: linguistic (e.g., 5-point Likert scale), boolean, or quantitative (which must undergo a min-max normalization to enable the downstream AHP). A systematic searching approach is required so that to ensure the traceability of the results collected from the available sources of information. During this step, pre-filtering criteria may be applied to avoid the database size increasing indefinitely (e.g., discarding obsolete devices).It is worth noting that technological databases may be already available in literature, possibly containing obsolete devices or focusing on different features; in this case, we suggest reusing the existing dataset, without disregarding the device identification step (to add new devices and cover all the features of interest).

3. Device filtering: it implies the general classification of the collected devices to shortlist the alternatives to examine in depth. Primary features are used to classify devices listed in the technological database. We exploit the standard AHP to assign different weights to features [19], so that adapt the decision process to different application scenarios. AHP is widely used in decision-making processes [20] and it applies pairwise comparisons between features. The importance of each feature with respect to all the other features is left to the judgement of domain experts, which assign priority weights by using the Row Geometric Mean Method [21]. However, different experts may disagree on the importance of features; to assess the inconsistency of expert evaluations, the methodology entails the analysis of the geometric consistency index [22], the consistency ratio (CR), and the overall dissonance (Psi). Finally, inconsistencies are mitigated by averaging the scores given by multiple experts.

Given the scores assigned to each feature in step 2, and their weights as computed by AHP, we can score and rank each device by computing the weighted sum of its features. We retain the best 20% of the devices for a further refinement step. The refinement is based on the qualitative evaluation of secondary features, given that these features are sometimes complicated to compare (e.g., price, SDK readiness), or a quantitative analysis requires much time (e.g., to assess the data accessibility). This step ends with the selection of the top-5 devices, sorted using the AHP method.

4. Device selection must allow the identification of the best device(s). When possible, testing the selected devices in a controlled environment gives the best insights about the practical usage of the devices in the real application. If this solution is not viable (e.g., because of the limited budget), a further selection is needed, based on the secondary features. For example, the battery duration could be a tiebreaker when dealing with long working shift, while the accuracy of the measured parameters is crucial in critical environments.

IV. Wearables selection for fatigue estimation

We applied and validated the proposed methodology for selecting a wearable device in an industrial application. The goal was to monitor worker's physiological data to enhance the human-in-the-loop control of a production system. The HDT is modeled using Clawdite, a flexible IIoT-based platform supporting the creation of HDTs [23]. Collected data must be reliable enough to feed an AI model that estimates the current worker fatigue level.

1. Features definition (validation): Our industrial application has the following requirements: *(i)* to collect workers physiological data to feed an AI-based estimating the perceived fatigue exertion; *(ii)* to transmit collected data from the device to an external platform in near real-time; *(iii)* to comply with an industrial environment characterised by dust, vibrations and shocks; *(iv)* to be non-invasive and comfortable for workers, with no obstructions; *(v)* to minimize the worn wearables. Given these requirements, we derived primary (highlighted in bold) and secondary features as follows:

- General characteristics: device type, wearing position, **screen presence**, **internal memory** (if any), battery duration (estimated) with or without active sensors (e.g., GPS), charging time, battery capacity, waterproof rating (IP or ATM), **weight**, and price.
- Communication protocols: **ANT+**, **BLE**, **Wi-Fi**.
- SDK: availability of an SDK supporting **real-time data streaming** directly from the device, or to communicate via a smartphone application, or other generic APIs enabling communication (e.g., **web platform availability**);
- Physiological metrics: capabilities to measure features relevant to the fatigue estimation, namely electromyography (EMG), electrocardiogram (ECG), bioimpedance, HR, HR variability (HRV), interval RR, peak to peak interval (PPI), skin temperature (ST), galvanic skin response (GSR) / electrodermal activity (EDA), blood pressure, oxygen saturation, volume of oxygen consumed per minute (V02 max), Pulse Plethysmogram (PPG).

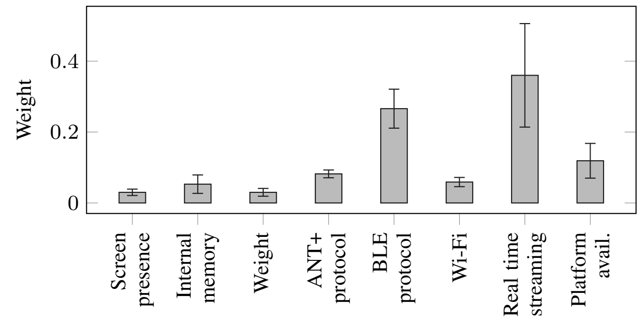

Fig. 2. AHP weights for primary features as provided by experts' evaluation.

- On-boarded sensors: presence of specific sensors, including HR meter, SpO2 sensor, pedometer, accelerometer, gyroscope, magnetometer, barometer, GPS, altimeter, thermometer, microphone, compass, ambient light sensor, optical sensor, NFC.

2. Device identification (validation): to build the technological dataset, we adopted an existing procedure to maintain the accountability of our website searching, which is typical for any multi-criteria decision-making problem [24]. We searched the Web for terms "smart band" and "smartwatch" and revised scientific articles, producers' websites, as well as comparisons and rankings available in blog posts. We limited the search scope to commercial and medical devices only. At the end of this step, the technological dataset contains a list of 110 wearable devices currently available in the market, along with their primary and secondary features. Each device in the dataset has been analysed individually by integrating pieces of information from several sources: manufacturers' websites, technical data sheets, manuals and online articles. Each of these characteristics individually contributes to determining the adequacy of the device for the identified application. In this classification, some features are not filled because of the limited information available (e.g., complete specifications are not released by some manufacturers). However, the classification is sufficiently wide to cover the scope of this research.

3. Device filtering (validation): Obsolete devices and those not fitting the application requirements has been removed from the dataset. We also discarded devices currently not available in the market. When different models of the same device are available, we prefer including the latest model only, because usually new models come with enhanced features, and new versions fix existing bugs. By applying the constraints above, the technological dataset has been reduced to 89 devices.[1]

We classified primary features of the remaining devices by adopting the AHP method. 5 experts assigned prior weights of primary features, as plotted in Figure 2. We applied AHP to score the devices based on their primary features relevance, and we retained the top-18 devices (20% highlighted in our dataset[1]). We then evaluated the 18 devices according to their secondary features. We paid particular attention to SDK usability, which was crucial for the data transmission

[1]The full version of the dataset is available at https://clawdite.spslab.ch/

development. The qualitative assessment led to the selection of 5 devices: Garmin Venu 2, Garmin Instinct, Polar H10, Garmin Vivosmart 4, Empatica E4.

4. Device selection (validation): We made a more in-depth analysis of the selected devices to reduce the number of wearables to wear. For this manual analysis, we considered the data format of the tracked parameters, as well as their granularity (i.e., acquisition frequency and possible aggregations). To assess the granularity, we used the available SDKs to inspect the collected data. Also, we maximized the number of measurable parameters, while minimizing the number of devices, paying attention to the specific measured parameters (e.g., HR is crucial in our application). After this analysis, we selected the Empatica E4 and Polar H10. The main reason behind this choice is in their complementary for the fatigue estimation. In particular, the first is a medical device measuring different parameters with a great accuracy, but, for this same reason, it does not provide continuous HR data if monitoring conditions are not reliable. Polar H10 (a chest band) fills this gap by providing very precise measuring of HR.

V. Conclusions

This paper provides a methodology for researchers and practitioners aiming to support the selection of wearable devices for I5.0 applications. We tested the methodology to select wearables for fatigue estimation in a real-world industrial application, with appreciable results. As future work, we plan to generalize the methodology to consider broader categories of devices (e.g., collaborative robots, Virtual Reality devices), not necessarily wearables but still targeting Monitoring, Supporting, Tracking and Training activities. The generalized methodology will be applied in a different project where the main goal is to monitor users using cameras instead of wearables. An interesting direction for this approach is to develop a hierarchical selection criteria, customized for specific applications. We will investigate also the integration of different multi-criteria decision-making techniques in our methodology (e.g., fuzzy approaches for qualitative judgements by experts, TOPSIS).

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