Efficiently Delivering Healthcare by Repurposing Solution Principles from Industrial Condition Monitoring: A Meta-Analysis

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1 Introduction

Societies around the world are aging. In the next few years, more old people will be treated and cared for. It is also getting more difficult to hire qualified staff and to motivate and keep them in the healthcare industry. Whether to succeed under these circumstances and how to succeed in a humane way will depend on automation, digitalization, and AI in order to meet the key results for the quality standard we want to preserve. The management and implementation of novel technological solutions requires integrating people from IT, engineering, and robotics. Managers who execute services in home care and hospitals also need to become more proficient in technology in order to make this happen.

In this context, a general perception might come in handy: Most technologies can provide benefits in a multitude of applications (Gruber et al. 2008; Penrose and Penrose 2009; Teece 1982). Thus, instead of reinventing the wheel, existing technological solutions might be applied in order to fill the current technology gap. In particular, patterns from industrial condition monitoring—as a leading sector regarding this application—appear to be usefully transferable into the healthcare and care service sectors.

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The main contributions of this work are: We provide concrete and conceptual impulses to those who have or want to improve effectiveness and efficiency in the care sector, i.e., R&D executives, managers of care facilities, and entrepreneurs. We also demonstrate the methodological approach of transferring technologies and solution principles from different domains to the care sector.

2 Methodology

The data of our analysis comprises the papers in the Web of Science Core Collection[1] that were published between 2016 and 2019 and whose title includes the term "condition monitoring." This has resulted in 1206 papers. To identify the different research trends in this basic population, we conducted an AI-supported cluster analysis. We employed tf-idf—"term frequency-inverse document frequency" (Rajaraman and Ullman 2011), a numerical statistic that reflects the importance of specific terms to a document relative to a collection of documents. We then identified concise terms in the respective papers, and on this basis, we modelled similarities between the papers.

The terms identified by tf-idf were next used for cluster naming, as well as names of papers with a small betweenness, i.e., a short distance to the respective cluster core. For each of the clusters, we then examined important research topics and the underlying functional principles. These principles should serve as a basis for the transfer of the respective conceptual idea to the care sector. Last, our interdisciplinary team identified potential benefits of the principles in the healthcare sector.

3 Results

Our study identified the 15 clusters depicted in Fig. 1.

One of the key problems in condition monitoring is that critical components are often difficult to access and therefore difficult to monitor. As a consequence, a lot of research deals with the question of which proxies can best be used to draw conclusions about the actual system states. A relatively simple approach is to make an input–output comparison that identifies efficiency losses, as is done for example with energy converters (cluster 3). Alternatively, wearing parts (cluster 4) or operating materials (cluster 11) can be analyzed.

An important proxy for the assessment of operating conditions is the emitted sound. By using microphones (or sometimes even radar systems; cluster 2), acoustic signals are detected from machine tools (cluster 5), gearboxes (cluster 9), roads (cluster 13), or diesel engines (cluster 14). Not only, but especially with acoustic analysis, AI approaches are used to identify faults by pattern recognition, e.g., in

[1] http://apps.webofknowledge.com.

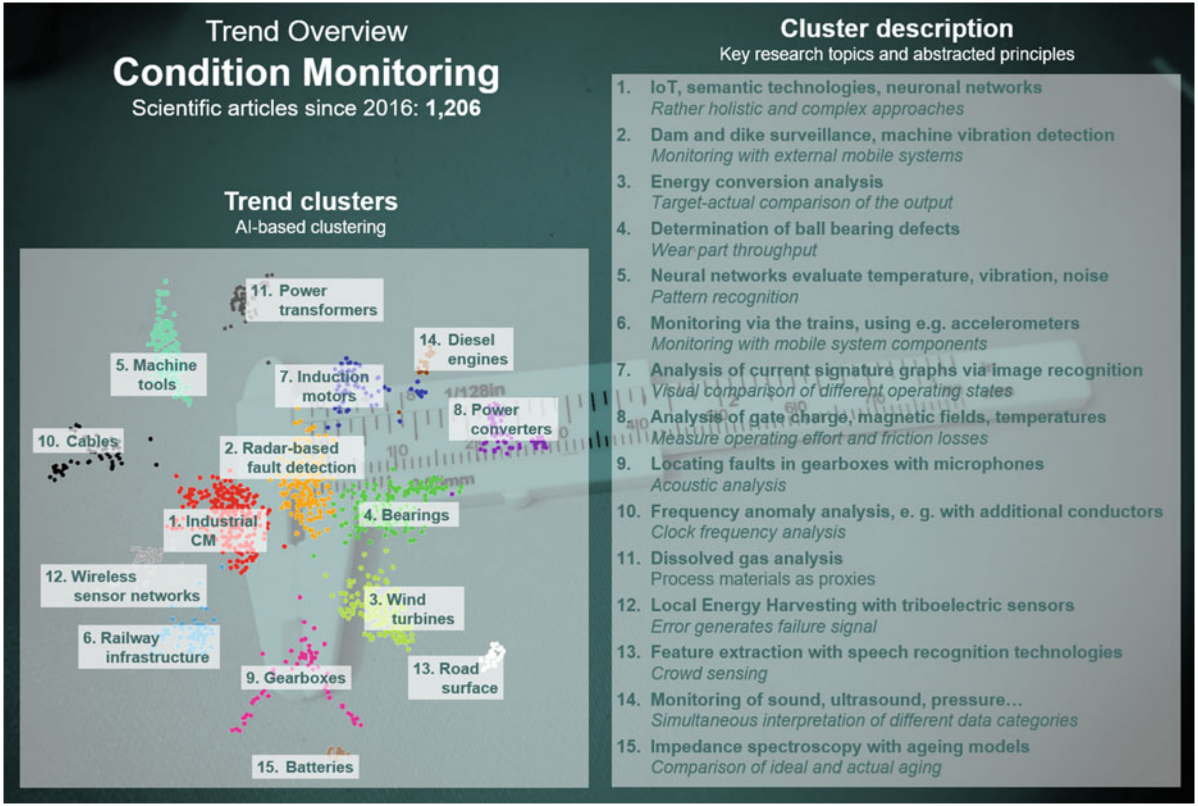

Fig. 1 AI-generated condition monitoring research topic clusters with abstract principles. Source: authors

industrial contexts (cluster 1), machine tools (cluster 5), induction motors (cluster 7), gearboxes (cluster 9), cables (cluster 10), road surfaces (cluster 13), or diesel engines (cluster 14).

In addition to the question of which proxy data to use for condition monitoring, the position of the sensors, their power supply, and the transmission of the measured data is often not trivial either. Thus, in addition to the radar systems already described (cluster 2), mobile system components are used, such as accelerometers in trains to monitor the rail infrastructure (cluster 6). Furthermore, triboelectric sensors are applied in the analysis of vibration data, where the power for data transmission is generated from the vibrations themselves (cluster 12).

A monitoring concept with a lot of potential is the use of sensors that are equipped with computing power for evaluation and communication options and that are mobile and often already available, e.g., in smartphones. For example, road surfaces can already be analyzed if there is simply a smartphone with speech recognition in the passenger seat (cluster 13).

3.1 Proposed Use Case: Comprehensive Home Care Monitoring

As home care patients are at home alone most of the time, they are particularly vulnerable and may not get help in time. For example, they may fall, suffocate from vomit, or die from a lack of fresh air (Komiya et al. 2013). We therefore suggest a comprehensive home care monitoring system that combines different sensors, such as motion sensors on patients, audio sensors for breath sounds monitoring, and air quality sensors. The sensor data needs to be constantly monitored for anomalous behavior. We suggest a deep neural network (Goodfellow et al. 2016) for this kind of task. (Artificial) neural networks are machine learning models that are loosely inspired by how the human brain works. A neural network is depicted in Fig. 2.

Deep neural networks consist of multiple layers of nodes (neurons) and are thus particularly suitable for learning hidden correlations in input data. There are already a number of related works in condition monitoring that can be adapted, e.g., an anomaly detection approach using wavelet transform and neural networks for condition monitoring of wind turbines' gearboxes (Cui et al. 2018) (cluster 3) and a neural network-based automated feature extraction method for anomaly detection in on-line condition monitoring (Roy et al. 2018) (cluster 4). Once anomalous behavior is detected, the system informs a nurse who can go to the patient's home and

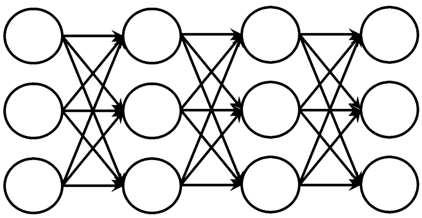

Fig. 2 Neural network connecting input nodes (left column) to output nodes (right column). Source: authors

provide assistance. We see great business potential for monitoring health of home care patients, as future healthcare will likely include more hospital-at-home models (Gebreyes et al. 2020).

3.2 Further Proposed Use Cases

In addition, further conceptual ideas derived from the condition monitoring domain that have the potential to bring benefits to care applications could be:

1. Mini drones at home that can fly to the head of patients and take probes of the sweat to analyze it in a miniaturized home laboratory (*derived from cluster 11*).
2. Monitoring the health of the staff in hospitals and private practices in order to check that they drink and eat enough, given their long working hours and work intensity (*derived from cluster 4*).
3. Intelligent mattresses that control the time spent in bed and monitor sleep quality and detect anomalous patterns, such as no use of the mattress for 24 h or not leaving the bed for 12 h. This would result in earlier alerts, earlier emergency services, and higher recovery probabilities (*derived from cluster 5*).
4. Predictive alert systems through combination of all data on an AI platform that is based on a cloud-based service with all data of the individual (*derived from cluster 14*).
5. Documentation of personal contacts of elderly people. This allows family members to do identity checks and history reviews (*derived from cluster 13*).
6. Laser screenings of eyes to detect problems at an early stage (*derived from cluster 7*).

Additional ideas that lead to a synergy of principles from the production industry, AI, and condition monitoring could be:

1. Self-driving (hospital) beds and chairs. As a consequence, care workers have more time for interaction with patients.
2. Drone-supported drugs delivery in hospitals through AI-driven mini drones that use the climate system infrastructure for transportation. As a consequence, care workers also have more time for interaction with patients.
3. Robotic arms that feed patients at home.
4. Condition care of mental capabilities through gamification implementation in tele-medicine.
5. Avatar interaction, similarly to tea time at home through a screen with an artificial partner.

4 Conclusions and Outlook

In this meta-analysis, we have pursued two main goals. First, we proposed novel and interdisciplinary impulses for decision makers and entrepreneurs in the care domain. In this vein, we provided the care community with the vitally needed use case on "comprehensive home care monitoring" as well as six further repurpose ideas. Second, we summarized the essence of industrial condition monitoring, i.e., 15 clusters of technological solution principles. We demonstrated that these look promising for transfer into and repurpose in the care domain. Future R&D work might use these insights by addressing further domains and transfer respective technologies and solution principles to the care sector. This will further make it possible to quickly and cost effectively deliver new products and services.

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