Week 6: Literature Review

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# Literature Review

## Who is the customer

A demographic timebomb will create significant pressure on the global health care system because people live longer, have fewer children, and medical costs continue to increase (Piggott, 2016; Stone, 2017). When patients cannot afford the required care, either the quality decreases or social programs must fund the difference. Demographic specialists predict that by 2050 nearly “80% of the global elderly population will be from low- to middle-income countries (Muhsin, Munyogwa, Kibusi, & Seif, 2020, p. 1).” Economic constraints within those countries will limit the effectiveness of their welfare programs and adequate services availability. Additionally, over one billion globally have a limiting disability that requires additional support (Morris, 2008). Medical facilities need mechanisms to defuse the situation by reducing costs and deferring the transition to an assisted living home.

## Challenges with current solutions

Inversely, the explosive growth across IoT, Cloud, Big Data, and Mobile (ICBM) is continuously decreasing costs and enabling new scenarios. These technologies will revolutionize the health care and wellbeing industries. Academic and commercial vendors are continuously delivering innovations across these domains. However, mainstream offerings primarily focus on measuring simple body metrics (Koreshoff, Robertson, & Leong, 2013). While these products provide incremental value, they do not move the needle. Nearly eight years later, the industry myopically drives toward wearable IoT devices (Tun et al., 2021). Researchers concentrating on these areas make sense due to the low barrier to entry. Though, that same ease is commoditizing the products available and stifling creativity.

Technology within special needs and elderly care settings has unique challenges and requirements (Ferati, Kurti, Vogel, & Raufi, 2016). For example, these solutions often support safety functions and require uninterrupted monitoring. Wearable IoT has inherent risks that the patient will disable or forget the device. This situation is particularly profound in patients with memory impairments like dementia (Wilson, 2017). Additionally, the obtrusive nature of wearable technologies makes them impractical for extended duration scenarios (Razzaq et al., 2020; Singla et al., 2010). Alternatively, specific vendors utilize Personal Digital Assistants (PDA) (e.g., Amazon Alexa) with voice commands. These products are an effective tool for setting reminders and recording activities (Tan et al., 2020). However, several scenarios cannot exploit vocal interactions, such as non-native speakers and individuals with vocal disorders.

Assisted living facilities use trained nurses to mitigate these issues. Having a human inspect the patient visually is an effective but expensive tool. The median compensation rate for registered nurses is $75,330 annually ($36.22 per hour) (US Bureau of Labor Statistics, 2020). Due to the high cost, few patients have private nurses and receive fractional supervision timeslices. Instead, patients could receive continuous observation at lower costs using Computer Vision. Artificial Intelligence and Machine Learning (AI/ML) models can observe patient behavior and react accordingly.

## Implementing unobtrusive systems

Amazon Go, a cashier-less store, proves the potential through its sophisticated computer vision technologies that can even protect against shoplifting (Wankdhede et al., 218). However, training these computer vision models requires domain-specific video clips (Das et al., 2019; Razzaq et al., 2020). Most open-source datasets contain outdoor and sporting activity, which is generally different from indoor behavior. Researchers are mitigating these issues by minimizing project scope (Yi & Feng, 2021; Chen et al., 2020). While this is acceptable during the proof-of-concept design, it will impact productization.

After creating the training video, perform Human Activity Recognition (HAR) through a two-step process (Razzaq et al., 2020; Chen et al., 2020; Yi & Feng, 2021). First, a process extracts the subject’s skeletal position from a given frame. This phase begins with decoding the information into RGB+D (Red Green Blue and Depth) matrices. Next, the researchers use Convolutional Neural Networks (CNN) to identify the body parts within the frame. If the room has multiple cameras, then a normalization process must build a consistent 3-D representation. The normalization needs to also account for noise and scaling challenges. These issues occur because the patient can freely move around the room. Microsoft’s Kinect Sensor supports automating this step to a certain extent. Alternatively, Carnegie Mellon University’s Open Pose library can approximate the 3-D skeletal structure from 2-D images.

Figure 1: Extract Skeletal Process

Second, a process needs to determine the skeletal changes by comparing the input 3-D skeleton against the previous frame’s position. After determining the delta movement updates, a recurrent sequence algorithm predicts the activity. The implementation is different between each publication (e.g., Dynamic Time Warping and Long-Term Short-Term Memory LTSM). However, the general strategy of using Recurrent Neural Networks (RNN) remains the same. After evaluating a sequence of skeletal movements, the algorithm will classify the action.

Figure 2: Movement Classification

## Scaling the classification process

It would be challenging to build one movement classification system that supports the entire universe of human activities. Instead, production systems blend hundreds of models into ensemble algorithms (Bell, Koren, & Volinsky, 2009). For example, predicting that the subject is picking up a fork, spoon, or cup is similar. The classifier can determine which subactivity compositing predictions the subject lifts an object and a standard object classifier.

Though, in practice, there can be issues programmatically choosing the correct composite models. One solution involves executing dozens of binary classifiers, then filtering the outputs using a voting scheme (Delgado, 2021). For example, three binary classifiers might exist to predict the subject is lifting an object. Then under a simple majority vote, the meta classifier equals the decision with at least two votes. System designers might require multiple voting schemes across the solution depending on the criticality of being right. For instance, if three classifiers are predicting the patient has fallen, one vote might be sufficient.

## Integrating AI/ML into the ecosystem

The most powerful artificial intelligence applications use machines to enhance human capabilities rather than replace them (Heer, 2019; Boire, 2017). For instance, a person can write a more profound business case than a machine; however, the same machine will have fewer misspellings and grammatical errors. This dichotomy exists because humans specialize in contextualizing thought versus automation uses patterns to make predictions (Schleer et al., 2019). Artificial intelligence is a tool that can automate mechanical tasks, pattern match data, and enhance human capabilities. Organizations can use these means to improve efficiency and reduce wastefulness. These innovations deprecate the need for specific skill sets and lower the entry barrier into other expert systems. While this causes an initial decrease number of jobs, entirely new industries follow shortly afterward. When a society can replace low-paying jobs with multiple high-paying industries, this promotion justifies the short-term pain.

For instance, a recent demonstration shows that AI/ML can map facial expressions to pain levels with 93% accuracy (Nugroho et al., 2018). These capabilities could enable every patient access to a well-trained and vigilant private nurse. Other publications chose to forward the observations to cloud services for remote management features (Elloumi et al., 2020; Chen et al., 2020). After centralizing patient telemetry, the nursing staff can more efficiently prioritize their time and resources.

## Including Cyber-Physical Systems

The Internet of Things (IoT) represents the next evolutionary step in communication and system connectivity. Naïve outsiders see this industry as a series of gimmicks, Apple watches, and Smart toasters. More importantly, those statements are factual and create the missing bridge between cyber and physical systems (CPS). This capability comes from sensor and input networks that emit telemetry into ubiquitous cloud computing and machine learning platforms. Using physical motors and actuators, artificial intelligence, and Big Data solutions can then reach back into manufacturing and safety systems. As information and decision processes transact across this bridge, organizations can execute expert workflows autonomously and prevent costly failures.

Health care solutions can leverage these bridges to offload specific nursing tasks to autonomous devices. For example, the computer vision processes might detect the patient is experiencing mild pain and dispense an aspirin (Amin, Salahuddin, & Bouras, 2020). Before dispensing medication, the CPS can optionally request authorization from the central nurse’s station. This design flexibility enables administrators to set guardrails and ensure consistency. While many health care CPS scenarios are easy to describe, they often span complex workflows. For instance, the aspirin dispenser involves computer vision, edge processing, cloud computing, manual approval steps (optional), and finally, orchestrating a medication vending machine. Different vendors with inconsistent protocols write these components, making secure and reliable service integrations challenging.

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