Week 6: Literature Review

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# Literature Review

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.

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.

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. Next, the movement delta changes feed into a recurrent pattern detection algorithm. **Left off here**

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.

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