Week 8: Elderly Care 2.0 User Acceptance Test Plan

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TIM-7241: Constructive Research Design

June 13, 2021

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# Elderly Care 2.0

## Problem Statement

Senior citizens live longer than ever and want to defer moving into nursing homes until later in life. Transitioning into elderly care comes as a double edge sword. On the one hand, nurses can provide 24-hour care. This assistance could mean the difference between life and death (e.g., during a fall). On the other hand, the services are prohibitively expensive, nearing $90,000 annually (Tan et al., 2020). Additionally, these facilities lack the personalization available within one’s home. Further, specific individuals with diseases like dementia and Alzheimer’s require even greater levels of attention.

Traditionally, addressing the situation requires increasing human capital, such as adding more traveling nurses or family member oversight. However, this solution increases health care costs and collects limited patient health samples. These infrequent visits might miss critical issues, especially with the most reluctant to relocate. Alternatively, researchers are exploring wearable IoT devices. Those sensors provide mechanisms for requesting assistance and receiving continuous monitoring. There are many limitations to wearable solutions, most notably that the person must remember to wear them, which raises concerns for early-onset memory loss patients.

## Building the Business Case

Many senior citizens want to remain in their homes and still receive the attentiveness typically found in assisted living facilities. When this gap narrows, it enables the patient to remain in familiar settings for more prolonged periods. That situation has numerous benefits, both psychologically (e.g., higher morale) and economically (e.g., deferring private health care costs). Medical facilities can address these challenges through real-time video monitoring services that analyze patient actions and recommend care. For instance, patients with memory impairment might forget to empty the dishwasher, take medication, or bathe regularly. These scenarios are challenging to address through wearable devices. However, through computer vision, an in-home camera system transforms into a watchful eye that spots those missing actions. After detecting an issue, the system alerts the person using Text-to-Speech (TTS) services (e.g., Amazon Alexa or Google Home).

Medical facilities also benefit from massive deployments of in-home monitoring systems. First, the in-home camera system tracks patient movements enabling early behavioral regression detection (e.g., reduced mobility). Next, centralized teams can provide higher-quality care to more remote patients. This configuration increases profit margins by reducing operational overhead (e.g., excess staff and fewer physical beds). When patient care issues arise, the system can prioritize and audit its resolution. The business can leverage this competitive position to avoid cutting corners and providing world-class care.

Additionally, having the option to remain in-home expands the caregiver’s addressable market. These populations include healthy widows, lower-income families, and even younger children with disabilities. While adult children might stress over putting their mother in a facility, they are more willing to pay for a low-expense monthly service. Lower-income households cannot avoid private health care and can only hope the public option is acceptable. Likewise, autistic children need additional oversight, not removal from the home. All three situations provide peace of mind to the families and improve their quality of life.

# Literature Review

## Just Walk-Out (2018)

Amazon Go enables customers to purchase goods from physical stores without requiring cashiers (Amazon, 2021). Their solution uses Deep Neural Network (DNN) algorithms that process real-time video streams. Wankdhede et al. (2018) assessed the system’s sophistication through a series of shoplifting test cases. Their malicious attempts to steal items failed, which provides evidence that real-time video monitoring is an effective real-world tool. Before engineers can transpose the solution directly into a person’s home, several critical changes are necessary.

## Consumer RGB-D Cameras and Applications (2012)

Action tracking systems require sophisticated machine learning algorithms that classify spatiotemporally movements. They typically follow a process that collects RGB+D (Color and Depth) camera frames and decodes them into 3-D space (Litomisky, 2012). Next, a series of filters must crop, resize, and align the principal subject. This step is necessary because people can freely move around the room. Third, a feature extract process outputs matrices representing the body’s location and orientation. Finally, those tensors flow into Long-Term Short-Term (LTSM) algorithms that classify the movement into gestures.

## Toyota Smarthome (2019)

Many general-purpose gesture detection libraries already exist for behaviors such as sporting events other high-energy actions. However, daily indoor activity tends to be more subtle and nuanced (Das et al., 2019). This discrepancy creates the need for purpose-built training sets that sufficiently cover patient-specific actions.

Sophisticated action tracking systems learn human actions through RGB+D camera frames.

First, machine learning algorithms require vast quantities of domain-specific training data. According to Snee (2015), there needs to be a minimum of ten examples per model parameter. The