Week 8: Elderly Care 2.0 User Acceptance Test Plan

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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, pose, 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 limits reusability and creates the need for purpose-built training sets that sufficiently cover patient-specific actions. These custom datasets necessitate vast quantities of examples with accurate labels, or the machine learning model will produce unreliable results. As a general thumb rule, each model parameter needs at least ten examples to avoid overfitting (Snee, 2015). Mechanisms exist for accelerating the process of building custom datasets (e.g., transfer learning). However, this is still an open research topic.

## Integration of SmartHome (2020)

After the system decodes the subject’s actions, it needs to act upon that information. While some responses are relatively trivial (e.g., dispatch an ambulance), other reactions must utilize Cyber-Physical Systems (CPS) to cross the digital boundary. Building these integrations is challenging as it draws upon knowledge spanning networking, sensors, embedded systems, and related concepts. Further, CPS devices lack standardization which impacts component reusability.

Elloumi et al. (2020) propose a Smarthouse Operating System (SOS) that provides core services such as identity management, system state, and message routing. Their blueprint also outlines several automation application profiles (e.g., heat management and fire detection). These capabilities enable developers to focus on their integrations value differentiation versus writing tedious generic code. The authors demonstrate the effectiveness of this approach using a CNC (Computer Numerical Control) machine to print a replica house (2 cubic feet).

## Privacy Enhanced Cloud-Based Facial Recognition (2021)

It can be helpful to think of identity within IoT as a profile of historical choices, stated preferences, user roles, and known associations (Wachter, 2018). When the device understands the user’s profile, the experience can be customized and produce more accurate predictions. The payment for access to these inferences and decision processes comes from personal information, such as calendars, contacts, and routines (Mickens, 2018). This trade creates privacy concerns that can be subtle and can go unnoticed for some time.

The monitoring system will collect intimate knowledge of its assigned patients and even capture private communications. Mechanisms must exist for protecting this information as it flows between different compute domains (e.g., local versus cloud providers). Yang et al. (2021) propose a Secure MultiParty Computation (SMC) model that locally encrypts sensitive images (e.g., faces). Afterward, it uses Cheon-Kim-Kim-Song Homomorphic Encryption (CKKS HE) to predict details about the protected payload (e.g., Bob’s face). These efforts suggest that the system minimize the amount of information that must leave the patient’s private network.

## Healthcare Monitoring using IoT (2020)

Software that takes advantage of cloud resources gains agility, elasticity, instantaneous provisioning, and cost management constructs. However, some businesses are reluctant to trust these environments entirely due to security concerns (Ali et al., 2015). Alternatively, systems engineers can deploy hardware appliances that bring cloud aspects into the home or medical facility. Abdulameer et al. (2020) propose and implement a small replica house (2 cubic feet) similar to Elloumi. This solution uses various wearable device sensors, Arduino micro-controllers, and one Raspberry-PI. Users can check their vitals and other health KPIs (Key Performance Indicators) through a web portal.

Provisioning small on-premise appliance makes sense and handles scenarios such as failures at the ISP (Internet Service Provider). Some benefits come from standardizing the control-plane versus assuming the patient’s computer is compatible with the proposed monitoring system.

# Examining Competitive Landscape

Abdulameer et al.’s (2020) design fixate on collecting metadata from wearable IoT devices. Tun et al. (2021) surveyed fifty-five recent publications that discuss IoT use cases within elderly care. Their findings suggest that nearly all search focuses on wearable devices, mobility, and Personal Digital Assistants (PDA). Researchers focusing on these areas makes sense due to the low barrier to entry. Compare the effort necessary to clone a FITBIT mobile app versus transform 2-D images into spatiotemporal movements. Another set of challenges originate from insufficient training data. Aside from Toyota’s (2019) open-sourced data set, few repositories (e.g., YouTube) contain appropriate training data. Lastly, numerous areas across health care are improvable on a $25 RadioShake budget.

These methods are iterative and incremental improvements. Instead, video-centric monitoring moves the needle by positioning a health expert in every room. This virtual nurse understands the patient’s behavior and can deliver semantic meaning.